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Publication Date

2006

**UNIVERSITY OF CALIFORNIA,
IRVINE**

Strategic Freight Transportation Contract Procurement

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil Engineering

by

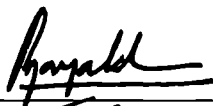
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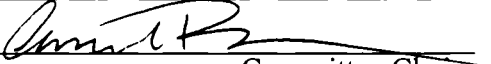
2006

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Committee Chair

University of California, Irvine
2006

DEDICATION

To

my grand fathers

Nandiraju Anjaneyulu

and

Karanam Venkateshwar Rao

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ACKNOWLEDGEMENTS

I express my heartfelt gratitude to my advisor, Dr. Amelia Regan, for her guidance, encouragement, and friendship over the past five years. The absolute belief she showed in my abilities helped me to get over the tough moments in the course of research. It was a pleasure working with Dr. Regan and a learning experience all along during my stay at UCI. Most importantly I really appreciate her help during paper deadlines and working on the drafts even on the weekends.

I thank my committee members, Dr. Will Recker and Dr. Jayakrishnan (Jay), for reading my dissertation and providing valuable suggestions and comments. Dr. Recker helped me to view research problems from different perspectives. The questions posed by Jay on my research problem contributed enormously to the final outcomes of this research. I would like to appreciate Dr. Mike McNally, for his guidance during the course of the dissertation and my stay at ITS.

I thank all my colleagues at ITS for their help and friendship. It has been great fun working with them. Riju and Andre made the hours I spent at ITS pleasurable with their with their discussions on research, sports and life in general. The help of Minyoung, Laia, Nesamani and Cindy during research is greatly appreciated. I thank my friends Ballu, Manish and Satish for making my stay at UCI enjoyable and supporting me during the critical times in my dissertation work.

I gratefully acknowledge the tremendous help provided by the staff at ITS and Civil Engineering. The financial support from University of California Transportation Center is gratefully acknowledged.

Finally I thank my family for believing and pushing me to pursue doctoral studies. I thank my younger brother Sekhar, for giving me advice on everything. I am deeply indebted to my parents Nandiraju Vara Prasad Rao and Vijayalakshmi for their sacrifices and encouragement, without which I would never have embarked on this truly wonderful journey. They have been my main source of inspiration and this dissertation is a tribute to their hard work and humility.

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ABSTRACT OF THE DISSERTATION

Strategic Freight Transportation Contract Procurement

by

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Doctor of Philosophy in Civil Engineering

University of California, Irvine, 2006

Professor Amelia C. Regan, Chair

Auction based market clearing mechanisms are widely accepted for conducting business-to-business transactions. This dissertation focuses on the development of auction mechanism decision tools for freight transportation contract procurement. The dissertation categorizes the problems in freight procurement auctions arising in both spot markets and long term markets. Spot markets are widely employed over the Internet using standard classic auctions. For long-term markets, large shippers (typically manufacturing companies or retailers) have begun to use combinatorial auctions to procure services from trucking companies and logistics services providers. Combinatorial auctions involve very difficult optimization problems both for shippers and carriers. In the US truckload market few carriers have the technical sophistication to

develop bids for combinatorial auctions. To address this problem we look at a different auction scheme termed a unit auction, where the shipper can exploit the economies of scope in the network and give the carriers the chance to bid on pre-defined packages similar to 'lotting' in supply chain procurement.

The problems in developing contract allocations, called the winner determination problem, are computationally complex and large-scale. Hence the development of good heuristics is of utmost importance. Shippers have non-price business constraints, which must be included in the winner determination problems to closely match shipper business objectives. We develop winner determination problem formulations incorporating the non-price business constraints and develop Lagrangian based optimization methods and greedy approximation algorithms for both unit auctions and combinatorial auctions. Extensive empirical results are provided to test the performance of the heuristics against a standard integer-programming solver.

Bidding in auctions from the carrier's perspective is complicated as it involves taking into account the competitive behavior of other carriers and a carrier's difficult network optimization problems. We develop bidding strategies for carriers in spot markets using concepts from economic auction theory. For long-term market bidding, we study the effects of demand uncertainty, competitive behavior, carrier network synergies and strategic pricing, and shipper's winner determination problems on carrier bidding using optimization-based simulation analysis.

CHAPTER 1 INTRODUCTION

This research examines issues related to freight transportation service procurement using auctions. Freight transportation is an important component of the economy. It enables the activities of production, commerce, and consumption by ensuring the smooth movement and timely availability of raw materials and finished goods. The value of the commercial freight transportation market in the US exceeds seven hundred billion dollars per year. Estimates of the market share attributable to truck transportation range from seventy to ninety percent.

The United States commercial freight transportation market exceeded \$1130 billion in 2003 representing approximately 10.3% of the Gross National Product (BTS, 2004). According to latest estimates, trucking industry hauls 68.9% by weight of all freight transported and an amount equal to 9.1 billion tons in the US. The total worth of the industry was US\$ 610 billion, about 86.9% of the US freight expenditure. Trucking industry for about 80% in the US is the sole means of freight delivery (ATA, 2003).

The trucking industry operates in a highly competitive market where profit margins are thin and service requirements are high. The two conflicting objectives, generating profits and providing good service must be met within the current paradigms of production and management, such as, just in time procurement, production and distribution and customer centric supply chains. The deregulation of the US trucking industry led to removal of barriers for entry of firms and ushered in a new era of competition among the carriers. Currently the freight trucking market is highly fragmented with many small

trucking companies and few large companies.

The deregulation of interstate trucking in 1980 and of intrastate movements in 1994 changed the relationships between shippers and freight carriers from transactional to contractual. Transportation procurement is the process by which shippers negotiate with carriers to satisfy the movement of goods between origin-destination pairs. Because of the advances in information technology and the rise in complexity of procurement logistics, optimization-based procurement using auction mechanisms is gaining popularity. Particularly noteworthy is the increase in software development to make the procurement processes paperless and also help carriers and shippers to use optimization mechanisms. The global logistics market is especially huge and complex. The time pressures under which these markets operate are extreme. Coupled with increased pressures of marketing and the change of consumer demands and preferences minute by minute, companies are trying to develop strategies to deliver the right products in a highly dynamic environment. Transportation service providers deliver the products to satisfy their demand. The participants in the transportation market are primarily shippers and carriers. Shippers are the retailers, manufacturers, distributors and other companies that need to move freight. Carriers are the trucking companies that own and control transportation assets. As with any industry there are intermediaries, for example the third party logistics (3PL), function as the bridge between shippers and carriers to match demand and supply of freight transportation service.

Traditionally, transportation procurement -- though complex -- was carried out haphazardly. The transportation manager in charge of shipper's freight movements

called or sent request for quotes (RFQs) to his core carriers to see if they could service the company's demand. Carriers analyzed the revenue and vehicle utilization generated by the shipments and provided the manager with price quotes. The process went back and forth until the shipper's transportation manager selected most suitable carriers. The process had the disadvantage that each shipment was examined at the individual level and that the shipper did not have knowledge about what the shipment meant to each carrier or if there were carriers outside the core group with the ability to offer better service. The carrier also depended on their core shipper base and did not know other means of marketing their services. The whole procurement process was riddled with economic inefficiency and hence auction mechanisms are being used increasingly for optimization-based procurement of freight transportation services.

In this dissertation we examine some of the issues related to the development of economically efficient auctions for transportation service procurement from the perspectives of both shippers and carriers. The research first studies existing freight marketplaces, which use auctions as a market clearing mechanism and gathers insights about the use of these mechanisms in practice. The growth and the acceptance of auction mechanisms for procurement is limited by the complexity of the difficult optimization problems to be solved by both the shippers and the carriers. The shippers' problems are exacerbated by the inclusion of non-price side constraints in their optimization problems. This research develops formulations involving side constraints and looks into mathematical programming based heuristics to solve them. To reduce the complexity faced by carriers, auction schemes were developed to simplify the problem from their

perspective. We present an analysis of these auction mechanisms and provide algorithms for solving the hard optimization problems encountered in the process. Carrier bidding strategies based on economic auction theory are also examined. To aid the development of collaborative ventures for shippers to use in auctions, an optimization-based framework is developed and payoff schemes using game theory are suggested to facilitate successful partnerships.

1.1 BACKGROUND AND MOTIVATION

Auctions are market mechanisms for allocating scarce resources to autonomous and self-interested agents. According to McAfee and McMillan's (1987) definition, an auction is "a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants."

Auctions have been used since time immemorial. The earliest report of an auction is found in the chronicles of Herodotus dated around 500 B.C. (Shubik, 1983). Since then, auctions have been used by governments and private entities to sell products ranging from works of art, fresh flowers, fish, tobacco, precious stones and real estate. With the emergence of Internet marketplaces, auctions have found widespread use as a method for supporting and negotiating the business transactions between sellers and buyers. Today almost anything of interest to any consumer can be found on Internet sites such as eBay and Amazon etc.

Auctions consist of two types of participants: auctioneers and bidders. The auctioneer invites bids to sell a good or buy a service and the bidders provide their bids to buy the

good or to earn the right to provide a service. An auction is characterized by bidding rules, market clearing rules and information feedback. Market clearing rules specify the allocation of items to bidders and the bidders' payment. The allocation rule is usually formulated as an optimization problem and generally referred to as the winner determination problem (WDP). An information revelation policy determines the process by which information is disclosed to participants during the course of the auction. Auction protocols can be mainly categorized in two forms depending on whether the current bid price and the identity of other bidders is known in every round. When each bidder knows prices and identities, we refer to the auction as open. Otherwise the auction is known as closed. For an in depth introduction to auctions, the reader is referred to Milogram (2002) and Vijay Krishna (2004). Combinatorial auctions are allocation mechanisms for the simultaneous offering of multiple heterogeneous items. Bids in these auctions are constructed for bundles of offered items. These auctions help bidders and auctioneers to gain economic efficiency by leveraging the synergies possible when bidding on bundles of items. Combinatorial auctions have been used in various industries and are especially predominant in trucking industry contract procurement (Caplice, Sheffi, 2003). Since the FCC (Federal Communications Commission) auction of wireless spectrum rights in 1994, many economists have examined the auction mechanism design problem in combinatorial auctions and are experimenting with various designs to reveal bidders' true valuation and achieve economic efficiency.

Transportation carriers can either be classified as "direct" or "consolidated". Direct carriers move between an origin to a destination without any intermediate stops for load

consolidation. The consolidated carriers such as Less Than Truckload (LTL) and package delivery carriers do load consolidation using break bulk terminals. Auctions mechanisms are predominantly being used for the procurement of direct transportation services. The auction mechanism applications for other transportation service sectors are few and far between, but nonetheless these are gradually emerging (see for example CombineNet, Inc. for ocean and LTL services and SAITECH, Inc. for LTL).

Transportation auctions have unique characteristics. The entity traded is a service and the demand and supply locations are geographically dispersed. The costs involved for direct shipping include line-haul costs (fuel, tires, operator wages etc.) and connection costs, comprised of deadheading costs and dwell time costs. Though the line-haul costs are well understood and almost the same for all carriers, the connection costs cannot be known with certainty because of the significant spatial and temporal uncertainties of freight transportation demand and supply. Transportation service procurement has three significant properties: economies of scale, scope and density. Lane interdependencies are created due to the above-mentioned uncertainties in connection costs. The overall cost will be lowered if a follow-on load is available after doing direct shipping and will be affected by the other routes the carrier is serving. The lane interdependencies create synergies among lanes. This is referred to as the “economies of scope” in transportation procurement. Economies of scale refer to the property in which the marginal costs are lower when operating higher volumes on a lane. Economy of density (EOD) is defined as the decrease in marginal cost caused by increasing the number of shipments in a network, while holding the network size and spread constant. TL carriers are sensitive to load

balance and so single lanes do not have economies of scale. According to Caplice (1996), lane balance in a network is achieved when the volume of inbound freight to one node is approximately equal to the outbound volume from a node in the entire transportation network. Auctions are one of the mechanisms widely used in theory and well as in practice for resource allocation, especially when the resources have uncertain or nonstandard values to the agents participating in business trading. Auction mechanism design for transportation procurement should take into account these three properties: economies of scale, scope and density. The questions that arise then are how should a shipper design auction mechanisms to procure carrier transportation services and how should carriers bid for business in these auctions?

Generic transportation procurement begins with bid preparation in which the shipper identifies the items (lanes) on which bidding will take place, the carriers to invite to the bidding process, the auction mechanisms and opportunities that exist for different types of shipper-carrier relationships. In the next stage, an exchange of bids and prices between the shippers and carriers takes place. In the final stage, all the carrier's bids are aggregated and analyzed and the shipper performs an allocation of the bids to different carriers. In traditional bidding methods carriers submit their bids on each lane in a single round auction and the winning carrier is the one with the lowest bid. One of the major problems with this setup is that the carriers have an incentive to hedge because of the uncertainty in the information provided to them. Also, bidding mechanisms do not take into account the interdependency of lanes, which creates economies of scope. Combinatorial auction mechanisms can reduce these problems. Shippers can reduce the

uncertainty and improve carrier operations by decreasing the loading and unloading time, minimizing dwell time and using advance shipment notices. The allocation problem for the shippers, called the Winner determination problem (WDP) is computationally complex and has been proven to be NP hard. Shippers' objectives include maximizing revenue, increasing the efficiency of the auction and the design of auction mechanisms which encourage the carriers to bid truthfully.

Caplice and Sheffi (2003) cited their experience in applying auction mechanisms using optimization-based techniques to help more than fifty companies procure freight transportation services involving more than eight billion dollars (US), and documented combined savings of more than five hundred million dollars to shippers. Moore, Warmke and Gorban (1991) describe the formulation of an optimization-based procurement bidding approach for Reynolds Metals. Ledyard et. al. (2002) presents a case study of Sears Logistics Services which, with the help of its consulting firms of Jos. Swanson and Co. and Net Exchange, conducted a multi-round combinatorial reverse auction for the procurement of contracts of serving over eight hundred lanes (delivery routes) and involving a cost of nearly US \$200 million dollars per year. Using this "combined value auction" method, Sears Logistics Services reported a 13% savings, which reduced its transportation procurement cost by US \$25 million per year.

In contrast to the iterative bidding process employed by Sears Logistics, Home Depot conducted a one-shot, sealed-bid reverse auction to procure services for its truckload shipments in the year 2000 with the aid of its partner i2 Technologies (Elmaghraby and Keskinocak, 2002). Additional applications of auctions, especially combinatorial

auctions in the procurement of freight transportation contracts include those employed by Wal-Mart Stores, Compaq Computer Co, Staples Inc., The Limited Inc. and many others (Elmaghraby and Keskinocak, 2002, Caplice and Sheffi, 2003). In addition to the above mentioned examples, many online marketplaces have emerged. For example, Freight-traders.com, Transplace.com, use an auction mechanism which mimics the traditional first price auctions in a spot market environment to satisfy unfilled or under-utilized capacities. Most of these markets have a first price auction, which is best lowest bid auction or a price-quality auction in a time-constrained environment. The price-quality takes into account not only price, but also other non-price attributes like historical servicing characteristics and reputation of the carrier bidding in the auction.

For shippers the problems to be tackled in a first price and second price auctions for a single object are easy. They just have to sort the bids based on ranks, costs and assign to the lowest bid price or best quality (Freight-trader.com). In auctioning off multiple heterogeneous lanes, difficult optimization problems need to be solved. In a combinatorial auction, the number of dependent bids of lanes made by the carriers is theoretically exponential. Even if the carriers bid, the process of allocation involves solving an NP-hard formulation. For a shipper, it is very important to have a tool that is able to perform “what-if” analysis by incorporating different sets of constraints at the system, lane level or a facility level. Such a tool involves solving different formulations, which need to be analyzed for generating optimal or nearly optimal heuristic solutions. In practice the shippers have to take into consideration various non-price attributes and include them in the optimization model (Caplice and Sheffi, 2003). The resulting

optimization problems become very complex. It is helpful to find good heuristics for these problems even at a loss of optimality, because the auctions take place in a time-constrained environment with small deliberation times. The other problem a shipper faces is that combinatorial auctions can become very complex for the bidders. The bid development process can take a long time and may be fruitless for the carriers. This leads to carriers not fully embracing combinatorial auctions. Plummer (2003) clearly draws this conclusion from his study of bidding practices for combinatorial auctions test cases. The shipper can simplify the bidding process for the carriers by developing the packages for them prior to the auction. In that case the problem of defining good packages falls on the side of the shipper. The shipper sometimes may want to do this to have more control over carrier operations or for expedited shipping. The problems involved in selling these pre-packaged bundles too involve solving hard optimization problems and as in the case of combinatorial auctions adding side constraints increases the complexity. Another problem faced by the shipper is the hedging of the bids by the carriers due to uncertainty in the procurement process, which require the auctions to be designed in such a way that the bidders bid truthfully. The shipper is also concerned with maintaining high levels of service during slacks and surges in demand for which robust allocation mechanisms to counter future disruptions are necessary.

While the majority of the research and commercial packages have focused more on solving the shipper's problem, the carrier's bidder's problem has received very little attention. The carrier faces uncertainty about a particular lane's value and the cost of providing service. This is particularly difficult for carriers if they want to incorporate the

effect of accepting a lane on the cost of serving future shipments. The carrier also faces inherent fleet management complexities with vehicle routing and scheduling problems in a dynamic and stochastic setting with time windows, penalties etc. The problems to be solved by the carrier are NP hard. Caplice (1996) presents some heuristic algorithms to create open loop tours, closed loop tours, inbound-outbound reload carrier packages, and short haul packages using potential savings estimates based on historical load volumes. Song and Regan (2003) develop optimization-based strategies for carriers to construct combinatorial bids. The shipper provides the carriers with disaggregate and highly stochastic demand data and the carriers have to factor in this stochasticity in the process of submitting the bids. The carrier has to make bids that will take into account the likelihood of winning a particular bid. The carriers need a balanced network with respect to prior commitments and the likely winning bid volumes. Inbound volumes should be in sync with outbound volumes at the regional level to achieve economies of scope. The stochasticity for the carrier is due to the uncertainty in demand and also the uncertainty in winning a particular bid. The problem facing the carrier is very complex even without introducing uncertainty but a methodology that incorporates the stochastic nature of the transportation services as well as the uncertainty of the actual award is necessary for effective bidding strategies.

In this era of heightened competition and stringent time constraints, many companies have in fact begun to collaborate with other supply chain partners to decrease their inefficiencies in operations and cut costs. Supply chain relationships are beginning to change from an adversarial to collaborative ventures and the transportation sector is

beginning to adopt similar policies to cut down logistics costs. Collaborative Transportation Management (CTM) is seen as the wave of the future. Combinatorial auctions have been widely accepted by the big shippers like Wal-Mart etc., but many small shippers have not been able to benefit from such auctions. However smaller shippers with similar business characteristics have begun to collaborate on shared auctions. Shippers have demands for transportation and the carriers the capacity to move them. Shippers and carriers converge at a neutral electronic marketplace (ex: Nistevo, TransCore) and the neutral arbitrator tries to find routes for shippers to collaborate. This collaboration leads to the elimination of deadheading by forming closed loop tours or continuous routes; the carriers' can transfer some of their savings by charging the shippers less. Thus collaboration becomes a win-win situation for both the carrier and the shipper. For effective collaboration, the shipper coalition must be such that it is mutually beneficial for all of them. It is essential to develop good payoff division schemes so that the shippers find the collaboration process a viable mechanism.

1.2 PROBLEM DEFINITION

In this research, we assume that truckload trucking transportation procurement is performed through an auction mechanism. The nature of processes for shippers and carriers in auction-based procurement are presented in the Figure 1.1. Shippers and carriers are the basic and distinct types of agents present in the framework. Shippers are buyers of transportation services. Shippers forecast shipment demand and their corresponding attributes like origin-destination, commodity type, stock out costs, time windows etc. Both shippers and carriers are rational agents in the sense that they want

to maximize their own revenue while achieving or providing necessary service levels. A contractual agreement between shippers and carriers involves a formal document that specifies price, length of contract period, commitments and penalties. The relationships are generally stable and are often long-term with periodic review. The shippers' problem is to procure services from the carriers for serving specific lanes (origin-destination pairs) in a least cost manner, while satisfying service level requirements and developing a strong carrier base for future procurement auctions. The shipper has information about the expected disaggregate demand over a planning period for which the auction is being run. The demands have both spatial and temporal characteristics. The carriers also have the demand of other shippers to satisfy and they bid in such a way so as to decrease the operational costs over their entire service network. The agreement specifies the price that carriers will receive for providing service to a specific origin-destination pair under agreed upon conditions. In long-term contracts, the shipper does not *guarantee* that the predicted demands will materialize and the carrier does not *guarantee* to move every load requested.

Truckload trucking involves door-to-door and mainly long-distance transportation. When a shipper calls, a truck or tractor-trailer combination is moved to a shipper-designated location, and a pickup of a full trailer is made or a trailer is loaded. The trailer is then moved directly to a specified destination. At the destination, the trailer may be dropped (and an empty one picked up) or the truck is unloaded, and the driver calls the dispatcher to give its position and request a new assignment. The dispatcher may assign a new load, ask the driver to move empty (referred to as a "bobtail", meaning a move without a

trailer) to a new location where demand should appear in the near future, or have the driver wait.

Truckload carrier operations thus evolve in a highly dynamic environment, where little is known with certainty regarding future demands, travel times, waiting delays at customer locations, and precise positions of loaded and empty vehicles at later moments in time. Service is tailored for each customer and the timely assignment of vehicles to profitable demands is of the utmost importance.

From a carrier point of view, the development of efficient resource management and allocation strategies is therefore at the heart of the management process. These strategies attempt to maximize the volume of demand satisfied (loads moved) and the associated profits, while making the best use of the available resources: drivers, tractor and trailer fleets, etc.

Carriers are agents with transportation assets. Each carrier is given the details of new service contracts including: demand forecasts (volume and distributions), lane details including each lane's pickup location, the delivery location; these may also include service time windows which specify earliest pickup times and or latest delivery times.

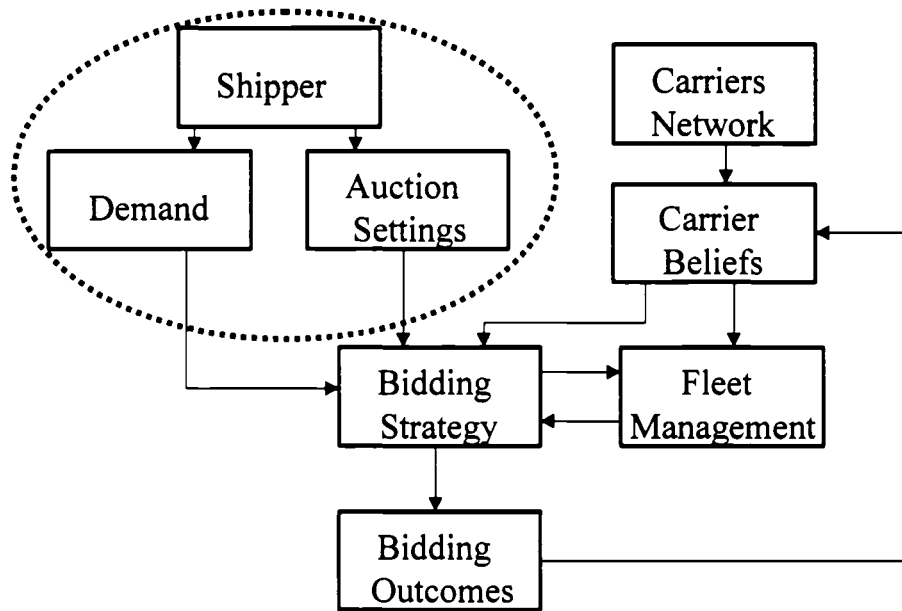


Figure 1.1 Auction market

Carrier behavior in auctions depends on beliefs about the shipper and other carriers, its own service network, shipper demand, internal infrastructure and fleet management. The main objectives of the carriers are to maximize profits, be a part of the shippers' core carrier base and to have a balanced network.

In auction based transportation procurement in a truckload market, the shipper acts as the auctioneer. The shippers' call for 'asks' (RFQ's) from the carriers to bid on their demand requirements. The carrier quotes its price and the shipper selects a carrier based on price and service quality. This is typically called a "reverse auction". The shipper has to decide what lanes to put out for bid, which carriers to invite, the information to be given to the carriers and the business constraints to be considered. Auction rules must take into account the incentive compatibility problem (removing carrier hedging),

demand interdependency (economies of scope) and the overall system constraints. Other auction parameters involve single sourcing versus multiple sourcing, single round versus multiple round, and information provided to each carrier in a multi-round setting. System constraints may include various non-price business constraints. For example, the minimum number of carriers to allocated, the minimum and maximum business the shipper should award, incumbency considerations, back-up concerns and threshold volumes. Shippers must identify the most critical business constraints to include in the optimization model and generate various scenarios to perform “what-if” analysis. The “what-if” analysis helps the shippers to capture the best allocation to fit their business constraints rather than simply the lowest possible cost assignment.

The carriers act as bidders and must solve their fleet management problem, taking into account the competitive environment and devise bidding strategies based on their previous auction experiences. After the auction awards are announced, the carriers analyze the winning bids and update their beliefs for future auctions. The main aim of the carrier in the auctions is to take advantage of the economies of scope, scale and density using the shipper’s demands in conjunction with its pre-committed transportation contracts.

For the carriers, the drivers of bidding in an auction are achieving network balance and fully utilizing their capacities. In a combinatorial auction, the carrier’s bid construction problem is that of evaluating the relative preferences over different combinations of new lanes, generating bids accordingly and identifying appropriate prices. The resulting bid generation consists of three basic elements:

- Bid Construction: The collections of bidding lanes and logical relationships between and among these collections must be determined.
- Bid Pricing Mechanisms: A carrier's reservation prices for each collection of lanes must be identified. The pricing scheme takes into account the probability of winning the bid and the behavior of other participating carriers.
- Volume Level Determination: A carrier may commit to serving all of a shipper's demand on each lane or some fraction of the total demand.

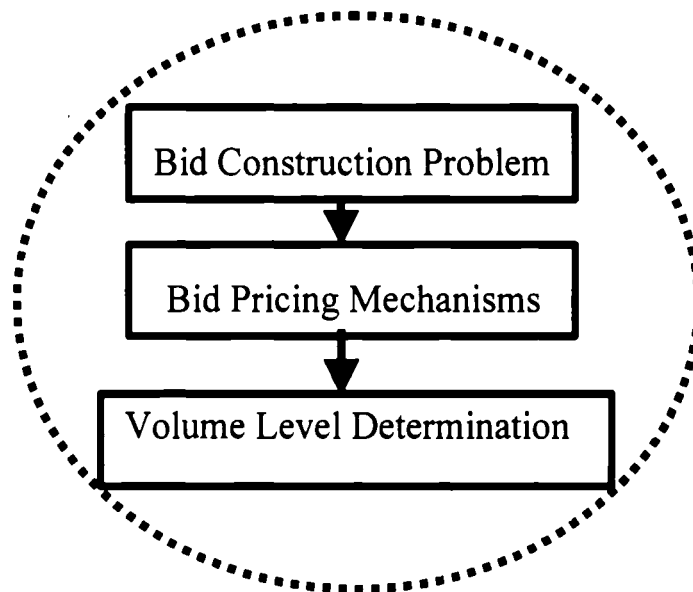


Figure 1.2 Carrier Bidding Strategy

The carrier's objective in such an auction is to find an effective strategy for estimating their valuations and preferences over any combination of new lanes and hence to construct their bids accordingly. The carrier's main focus is to obtain lucrative contracts on lanes on which its operation can be efficient. This is particularly important when a carrier has pre-existing commitments to other contracts at the time of the auction.

The complementary or substitution effects among new lanes and between new lanes and currently contracted lanes complicate the matter and must be expressed as logical relationships. Carriers also have to take into consideration the effects of their competitor's bidding strategy and their own valuations while generating bids. After the auction ends, it is left to each carrier to determine the optimal way to operate the new lanes awarded to them, combined with their current lanes at a minimum cost.

1.3 RESEARCH OBJECTIVES

This research examines issues facing shippers, carriers and third party logistics companies participating in auctions for freight service contract procurement.

1.3.1 Shippers Perspective

Shippers must decide the format and rules of the auction, the information provided to carriers and the business constraints to include. It is often the case that non-price business constraints are very important. Some examples are the minimum and maximum number of winning carriers, the minimum and maximum business they should award to a single carrier, preference for incumbent carriers, etc. The addition of these business constraints to the optimization problems increases the difficulty of the already complex allocation problems. The addition of the business constraints helps the carrier to find the best assignment of carriers to meet his overall system objectives rather than the lowest cost allocation. Shippers need faster heuristics or optimal solution procedures to allocate the awards in a time constrained environment. Shippers also must cope with stochasticity

arising out of the uncertainties in demand, network performance and carrier operations.

In this research, we develop a basis for scenario management for the shipper to include the system constraints. Mathematical formulations are developed involving the system constraints and provide Lagrangian relaxation heuristics to solve them. An in depth analysis of the Lagrangian algorithms and several greedy heuristics is presented. Another problem we examine is to reduce carrier bidding complexity in combinatorial auctions. We develop unit auctions, in which the shipper creates the packages a priori. Unit auctions are analyzed at length and we provide mathematical formulations that incorporate the non-price business constraints. Lagrangian Relaxation heuristics are developed using different non-price constraints and under different auction settings.

Combinatorial auctions with non-price business constraints for reverse auctions are formulated and the Lagrangian solution procedures are presented. Greedy and dual heuristics are developed and problem reduction techniques are examined. The algorithms developed are tested against the standard CPLEX solver.

1.3.2 Carriers Perspective

The carriers face stochasticity due to uncertainty in demand, shipper behavior and the need to satisfy their own network balance. The problem of bidding is NP-hard (Song and Regan, 2003). The problem facing the carriers is compounded because of the uncertainty in winning the bids and the information they receive from the shippers. The carrier has to take into account the probability of winning the bid in the bid generation

problem. The complexity of the carriers bid construction problems increases in the case of simultaneous auctions run by multiple shippers. We develop formulation to develop carrier bids from a strategic point of view, which helps to estimate the volumes to bid on each lane. From an operational perspective, we develop set-covering formulations which incorporate the probability of winning, the uncertainty of demand and supply and the competitive nature of auctions using economic auction models of bidding including private value and common value models.

1.3.3 Shipper Collaboration

Shipper collaboration involves an intermediary, a third party logistics (3PL) company or an online auction marketplace, which enables collaboration between groups of shippers with transportation needs. The problem can be viewed from a strategic or tactical perspective, giving rise to different formulations. The problem is formulated as a set-packing problem and tackles issues related to cooperation that face members of the coalitions from a game theory perspective. The challenge is to find a suitable collection of demands such that shippers collaborate and the number of vehicles used is minimized. Using concepts from game theory, we develop payoff mechanisms, which are in the core of the cooperative game, generating Pareto efficient solutions.

The primary contributions of this research are as follows:

1. The prevalent auction mechanisms in the transportation industry and the limitations of these mechanisms are examined.
2. Participating in full combinatorial auctions is difficult both for carriers

and shippers. We therefore develop Unit auctions and solve various winner determination problems in these auctions.

3. Mathematical programming based heuristics for tackling the winner determination problems in the combinatorial auctions involving non-price business constraints are developed.
4. The problem of improving the bidding schemes for carriers from a strategic point of view to secure balance of flows in the carrier transportation network is examined.
5. The issues facing shippers involved in collaborative auctions are explored.

1.4 OUTLINE OF THESIS

The thesis focuses on some of the issues in transportation freight service procurement both from the shipper and the carrier side. The perspective in the thesis is that of a neutral matching agent, for example a third party logistics firm (3PL) as the link between the shippers and the carriers. The goals of this dissertation are to develop viable auction mechanism designs and to improve the carrier bidding processes. After this introductory chapter, the rest of the thesis is organized as follows.

Chapter 2 provides a brief review of auction mechanisms and the relevant underlying theory from an economic and game theory point of view. In this chapter we provide an auction schema for transportation freight service procurement. We look at different classification of auctions and give insights of their application to transportation

procurement.

Chapter 3 reviews the prevailing practices of transportation auction marketplaces in the industry. E-commerce facilitates the reduction of supply chain intermediaries and reduces transaction costs and this revolution has spawned a number of marketplaces for freight transportation service procurement. This chapter examines the business models of existing freight marketplaces and the strategic behavior of shipper and carriers. A literature survey of market clearing mechanisms models for freight transportation market places is provided. Models for shipper-carrier strategic interaction are presented. Some key research questions related to developing methodologies to aid both shippers and carriers are discussed.

For many years, large shippers have deployed a variety of business-to-business auctions to procure transportation services from common carriers based on periodically renewed contracts. In chapter 4, we describe an auction mechanism design for shipper-defined packages, which we call unit and multi-unit auctions. We describe mathematical formulations for the winner determination problems in these auctions and employ a Lagrangian relaxation with subgradient optimization framework to solve the problems.

Chapter 5 considers the bid analysis problems faced by shippers involved in combinatorial auctions for the procurement of transportation services with additional shipper's non-price business constraints. The bid analysis problem in combinatorial auctions is a very difficult problem and the shipper's non-price business constraints further complicate this matter. This chapter examines this problem by formulating the shipper's business constraints, namely min- max carriers and favoring of incumbents,

as side constraints in integer-programming models. Two different formulations are presented to tackle this problem based on the differentiation between "contracts" and "loads". The assumption is that a contract is a unit and modeled as binary variable as a single sourcing decision. The "loads" help in the multiple sourcing decision-making and are modeled as continuous variables. Lagrangian relaxation based algorithms are developed to solve the bid analysis problems. The experimental performance of this approach is analyzed with empirical benchmarking on a set of randomly generated problems.

In chapter 6, we review the bidding models for freight transportation procurement in transportation auctions. The paper surveys the current literature on auctions and bidding and presents a framework for the consideration of bidding in truckload markets. We also examine volume based contracts as opposed to the unit lane contracts examined thus far. The chapter presents formulations to help carriers develop network balance using the classical transportation problem.

In chapter 7, we study the problem facing an intermediary, a third party logistics company or an online auction market of achieving collaboration for transportation demands that are to be satisfied from a group of shippers. We formulate the problem as a set-packing problem and tackle the co-operative issues facing the coalitions in the problem from a game theory perspective. The problem is to find suitable collection of items such that shippers collaborate and the number of vehicles used is minimized. Here we are only interested in finding the collaborative routes and make an assumption that these routes will be assigned to the carrier using auction mechanisms. In this chapter,

we also devise simple payoff mechanisms, which are at the core (from a cooperative game theory perspective) of the collaboration problem.

The thesis ends with chapter 8, which includes a summary of the dissertation including the research objectives, proposed methodologies, contributions to the literature, conclusions and future extensions.

CHAPTER 2 TRANSPORTATION PROCUREMENT

In this chapter we present fundamental concepts of auctions theory and provide the necessary tools required for understanding the dynamics involved in auctions. We also develop an in-depth literature analysis of classical auction-based mechanisms applicable to freight transportation contract procurement. We review the transportation market and discuss how auctions can be applicable for freight procurement. Finally we review and summarize the important factors related to the design of auction-based mechanisms in freight procurement.

2.1 AUCTION THEORY

An auction is trading mechanism used when sellers face many buyers. The trading of goods using auctions has increased due to deregulation of certain industry sectors and the growth of the Internet (Pekec and Rothkopf, 2003). Use of auctions is predominant in deregulated industries. Some of the examples are the sales of rights of the radio spectrum by FCC, electricity auctions and stock market trades. Industrial procurement, the purchasing of raw materials is also being done using auctions. Individuals as well as businesses buy and sell goods in auctions using a variety of sites like Yahoo, eBay, Amazon etc., making it a fairly mainstream phenomenon. The main goal in these auctions is to facilitate decentralized resource allocation. According to Kalagnanam and Parkes

(2004), this problem is different from classical optimization as the allocation problem depends on eliciting the true value of the agents (both sellers and the buyers). The problem therefore is to provide incentives so that the buyers will reveal their true preferences and an optimal allocation will occur. Classic auctions like First price, English, Dutch are being widely employed for auctioning a single item. The other problem is how to auction multiple items with multiple units. The problem becomes more complex when the valuations of an item depend on winning other items in the auctions. The objects in auctions usually have multi-dimensional attributes and the allocation mechanism should reflect these attributes.

Auctions generally have players (auctioneer and bidders), objects to bid on, players' payoff functions and bidder strategies. The object may be a single quantity or multiple quantities of divisible or indivisible objects. Examples for divisible objects auctions are energy auctions and indivisible are FCC auctions for the radio spectrum rights. The value of the objects to each bidder usually varies. The bidder's payoff functions are determined by the allocation mechanisms, reservation prices, other costs like entry, information gathering costs etc. Assuming rationality, players choose their strategies to maximize their expected gain. (Engelbrecht, 1980).

Depending on how the auctions can be used, the auctions can be classified as open or closed auctions. In open auction, the bidders receive the feedback on the provisional

allocation of the bidding items. In a closed auction, there is no information feedback to the bidders. Open auctions are also called oral auctions or open cry auctions and typically occur in multiple-rounds. Closed auctions are also called sealed bid auctions. The outcomes of the auctions are heavily influenced by the strategic behavior of the bidders and the sellers, the presence of asymmetries and independence of the private information. Each bidder has a private valuation of the objects that they are bidding for depending on the utility of the object for their purpose. This information can either be dependent on either some knowledge about the valuations of other bidders or completely independent of other bidders. Symmetry in an auction implies that all the valuations are drawn from the same common probability distribution whereas asymmetry deals with situations where each bidder has a different probability distribution to choose their valuation. Milgrom, (2004) and Vijay Krishna, (2002) are two good references for a thorough introduction to auction theory.

Four classic auctions are found in the literature.

English auction: English auctions are open, ascending-bid auctions. In this mechanism, the bids are made in ascending order and are made by the bidders until only one bidder remains. The payment scheme is for the winning bidder to pay a price equal to their bid.

Dutch auctions: A Dutch auction is an open descending bid auction. The name comes from the use of these auctions to sell flowers in the Netherlands. Initially, an

auctioneer quotes a high price and then the price is incrementally lowered. The auction stops when a bidder accepts the current price. Google.com issued initial public offering of shares using a modified Dutch auction (www.google.com).

First price sealed bid auction: As the name suggests, this auction is a closed auction. The prospective buyers submit a sealed bid taking into account their valuation and competition from rival bids. The bidders do not have any knowledge of the competitors' bids. The bidder with the highest bid wins and pays the price equal to the winning bid. Examples of first price sealed bid auctions are those for rights to off-shore drilling and mineral rights.

Second price auction: This is also called the Vickrey auction. This is a closed price auction and the procedure is similar to the first price sealed bid auction. The only difference being the winning bidder pays an amount equal to the second highest bid (Vickrey, 1961). Vickrey auctions are theoretically significant but are not used widely because of their susceptibility to cheating by auctioneers. However, there are some important current examples including eBay (Roth and Ockenfels, 2002).

Double auctions: In double auctions, several (or many) buyers and sellers submit bids and offers. The buyers submit bids for with unit prices of an item and the sellers can counter with their selling price offers. An agreement is made when the seller accepts the bid or the buyer accepts the offer. Stock markets typically conduct this type of auction. NASDAQ uses a double auction (NASDAQ).

Classic auctions can be used with a number of variations. The first being one in which the auctioneer suggests a reserve price and discards all the bids lower than that price. The auctioneer can have entry charges for bidder participation. The auctions may be constrained by time, which is typically the case of Internet based auctions (eBay for example). The auctioneer can set minimum increments at every round in English auctions. Generally the auctions are used to sell a single item but can be adapted to sell multiple units of the same item.

Auctions have been one of the important pricing mechanisms or system of allocation in especially deregulated industries (which are more driven by competition). In a deregulated industry for example electricity, radio spectrum, stock markets, etc., an auction mechanism offers a self-regulatory mechanism without regulatory constraints. In the airline industry, airport slots are allocated using auctions. The takeoff slot at an origin is reliant on the destination airport-landing slot. Grether, Issac and Plott (1981) develop a procedure to auction the slots using sealed bid auctions and an oral double auction. Rassenti et. al. (1982) proposes a combinatorial sealed bid auction to allocate slots to the airlines who submit package bids based on the compatible flight itineraries.

Federal Communications Commission (FCC) use auctions to sell licenses electromagnetic spectrum. FCC uses a simultaneous multiple round (SMR)

auction in which all licenses are available to bid throughout the entire auction. SMR auction have discrete, successive rounds with a pre-defined length of each round. SMR also allows combinatorial bidding, enabling the bidders to place bids on groups of licenses as well as individual licenses (FCC, 2005). The New York Mercantile Exchange, Inc., is the world's largest physical commodity futures exchange and the preeminent trading forum for energy and precious metals and it uses auction mechanisms for trading of cash, options and futures contracts (NYMEX.com). Federal Energy Reserve Committee (FERC) has conducted several auctions for selling natural gas transportation pipeline capacity using auctions (FERC, 1998).

2.1.1 Auction Mechanism Design

The auction mechanism design problem, the question of how to specify auctions formats and rules in order to induce participants to bid their true values and achieve economic efficiency, has been a topic of interest in auction theory for many years (Song, 2003). According to Kalagnanam and Parkes (2004), mechanism design is to “solve distributed allocation problems with self-interested agents by formulating the design problem as an optimization problem”.

Mechanism design involves defining feasible *strategies*, using a particular allocation rule and a payment scheme to select winners and payments (Myerson, 1984). The main aims of mechanism design are allocative efficiency and payoff maximization of a

particular agent. Allocative efficiency is achieving an allocation that maximizes the payoff of all the agents in the auction and is also termed the efficient mechanism design problem. This resembles the social welfare criterion in microeconomics. Payoff efficiency maximizes the payoff of one particular agent, usually the auctioneer and is called the optimal mechanism design problem. Mechanisms can be classified into two types: direct and indirect. In a direct revelation mechanism, agents are asked to report their true valuations. In an incentive compatible direct mechanism, the best strategy of the agent is to report the true valuation. Such mechanisms are much more computationally complex than general allocation mechanisms. Designing a direct revelation mechanism is hard; hence an indirect revelation is preferred in most cases. In a transportation auction shippers benefit from having carriers bid their true valuations but the profit margins are too thin to warrant the development of more complicated incentive compatible auction mechanisms. For a thorough introduction to auction mechanism design the reader is referred to Kalagnanam and Parkes (2004) in online electronic markets and Nisan and Ronen (2001) for algorithmic mechanism design.

Properties desired from an auction:

- ***Equilibrium:*** This is defined as the state at which no agent wants to change their bid given the information known about other agents. Different kinds of equilibria can be used for example, Nash, Bayesian Nash and dominant strategy equilibria.
- ***Efficiency:*** Given a set of allocations, under Pareto efficiency no one agent can

improve their allocation by making at least one another agent worse off. Under Allocative efficiency the total utility of the bidders are maximized.

- **Individual rationality:** Under Individual rationality no bidder can be worse off after participation than before. Another way to say this is that ex-post utility must be non-negative for every participant.
- **Budget balance:** Weak budget balance implies that the auctioneer has non-negative revenue from the auction and strongly budget balance implies that the auctioneer's revenue is positive.
- **Incentive compatibility:** Incentive compatibility implies that it is in the bidders' best interests to bid their true valuations. Such mechanisms are called "strategy proof". Incentive compatibility is very good for auctioneers and bidders because the auctioneer knows the how much each agent values the item and the bidders bidding complexity is reduced.
- **Solution stability:** Solution stability prevents collusion, meaning no subset of agents could have done better by forming a clique.
- **Revenue maximization or cost minimization:** A seller is the auctioneer who wants to maximize the total revenue. If the buyer is an auctioneer, then the problem is to minimize the costs.
- **Low transactions cost:** cost to participate in the auctions should be less and also hasten the auction allocation process to avoid costs.

- ***Fairness***: need to produce an allocation that is deemed fair by the participants as all bidders have an equal opportunity to buy the item being sold. Bidders' who lose because a different WDP algorithm would have made them winners may feel unfairly treated.

2.1.2 Auction Literature

In this section we present a brief review of the relevant literature on single item, multi-unit, multi-attribute and combinatorial auctions.

Single unit auctions: In single unit auctions, bidding price is usually the predominant factor in the allocation decision process. Firms typically use a sealed bid tender to decide the winning bid. If a first price mechanism is used then the highest bid price is used while if a second price mechanism is used then the winning (lowest) bidder will be paid the second lowest bid price (Vickrey, 1961). Literature on auction theory developed following a seminal paper by Vickrey (1961) in which he compared first price and second price auctions. The reviews by Engelbrecht-Wiggans (1980), McAfee and McMillan (1987a), and Maskin and Riley (1985) provide an introduction to auction theory, review the state of the art up to that time and convey many key ideas in bidding strategies. Milogram and Weber (1982) and Engelbrecht-Wiggans (1983) are excellent references for simple single object auctions. An important feature of these auctions is the existence of the revenue equivalence theorem, which states that English, Dutch, First price and

Vickrey auctions yield the same average utility for the buyer in single item auctions under a symmetric private values model (Wolfstetter, 1996). Under these auctions, the winner determination problem is easy to solve but the valuation problem faced by bidders can be very complex. The strategic complexity of predicting the behavior of other bidders can be very difficult.

From point of view of this research the most relevant branch of auction theory is the optimal auction design problem. Myerson (1981) and Riley and Samuleson (1981) roughly simultaneously studied this problem. Myerson's study is especially important for this research as he reports that the optimal auction design problem is equivalent to a relatively simple constrained maximization problem for a single object model. His formulation maximizes the sellers expected revenue with constraints based on participation (or individual rationality), that each expected bidder receive a non-negative expected surplus from participation and incentive compatibility which implies that it is equilibrium behavior for bidders to reveal their true valuations. Myerson(1983) gives a detailed review of research in optimal auction design. Bulow and Roberts (1989) present the analysis of optimal auction design purely in terms of a microeconomic based approach.

Multi unit auctions: Auctions involving the sale of multiple units of the same object are called multi-unit auctions. In transportation auctions a 'lane' or an origin destination pair

with a predicted (weekly, daily) demand volumes is the object for bidding. The literature on the simultaneous sale of multiple units is less well developed compared to the single unit case. In a volume discount multi-unit auctions, a single buyer and multiple sellers wish to exploit economies of scale using a volume discount auction. Here we have to select a set of winning bids, where for each bid we select a price and a quantity so that the total demand of the buyer is satisfied at minimum cost. In these auctions the non-price business constraints can involve an enormous computational burden (Davenport, Kalagnanam, 2000). Wilson (1979) first studied simultaneous auctions for the multi-unit case for stock trading auctions. Maskin and Riley (1989) extend Myerson's analysis of optimal auctions for a single item (1981) to the multi-unit case in which buyers have downward sloping demand curves, independently drawn from a one-parameter distribution, for quantities of a homogenous good. Such curves imply that the price decreases as the quantity purchased increases. They also develop expositions of revenue equivalencies for the multi unit case, when buyers each want no more than a single unit.

Palfrey (1983) analyzes sellers' (and buyers') preferences between bundling heterogeneous objects and selling them unbundled. Weber (1983) and Maskin (1989) study issues that arise in sequential multi-unit auctions. Vickery (second price) auctions are efficient in private value multi-unit contexts. Dasgupta and Maskin (2000) and Perry and Reny (2002) show how to generalize the Vickery mechanism to achieve efficient in a wide variety of multi-unit contexts. Jehiel and Moldovanou (2001) obtain results showing that efficiency is not usually possible when each bidder's information signal is multi-

dimensional, as is natural when there are multiple heterogeneous goods with interdependent valuations.

Multi attribute auctions: Procurement decisions usually involve multiple criteria for pre-selecting the carriers. Multi-attribute auctions relate to items that can be differentiated on several non-price attributes such as quality, delivery date, color, weight etc (Bichler and Kalagnanam, IBM Research Report). Commercial software has been developed to assist with this task. Some examples are Ariba, Freemarkets, Procuri and i2. Transportation auctions are multi-attribute auctions in the context that bidding items have other non-price attributes like service quality and delivery time windows and other business constraints. In order to evaluate bids for an item with different attribute levels a common approach is to use established decision analysis techniques. In basic techniques like linear, weighted utility functions preferential independence is assumed, so that an agent's valuation for a bundle of attribute levels is a linear-additive sum across the attributes. Other methods in use for modeling interaction among attributes are multiple criteria decision analysis (MCDA) such as multi-attribute utility theory, analytic hierarchy process, etc.

Combinatorial auctions: In this section we look into opportunities that take complementarities into consideration while purchasing. A combinatorial auction is a price discovery mechanism designed to provide flexibility and freedom for bidders to

express their preferences over complementary bundles of products or services. The allocation optimization problem solved by the auctioneer is a weighted set covering problem and is well known to be NP-hard. In order for bidders to express their preferences for bundles of items a bidding language must be introduced in order to allow for complex logical expressions. A bidder might ask for an XOR bid of two items, which simply means she would accept any one of these two items for their respective bidding price but not both. We call these two items substitutable to this bidder. A set of items can also be complementary to a bidder if she bids for a combination of these items as a whole, but will discard this bid if only one or part of them is awarded.

The concept of combinatorial auctions was proposed as early as 1976 for radio spectrum market (Jackson, 1976). Rassenti, Smith and Bulfin (1982) proposed a sealed-bid combinatorial auction for the allocation of airport time slots to competing airlines. Most recently, researchers and practitioners are applying combinatorial auctions in many broader fields. Those include but are not limited to: the procurement of railroad segments (Brewer, 1999), resource scheduling in manufacturing information systems (Kutanoglu and Wu, 1998), computer network routing (Hershberger and Suri, 2001) and auctions for airline seats (Eso, 2001). However, combinatorial auctions include many hard problems that could limit combinatorial auction applications.

In the combinatorial auctions with Vickery-Clarke-Groves (VCG) pricing (payments) the

dominant strategy for agents to report their true valuations (VCG is incentive compatible). The auctioneer solves the WDP for optimal allocation and solves a set of WDP for optimal allocation excluding an agent each time. The payment a bidder or an agent has to make is the difference in “welfare” of the other bidders without him and the welfare of the others when he is included in the allocation. VCG impractical to implement when number of bidders are large. In fact Krishna and Perry (1997) prove that the optimal auction that is also efficient is the Vickery-Clarke-Groves scheme. The calculation of VCG payments is an ongoing research topic. In Resource Allocation Design (RAD) mechanism by DeMartini et. al.(1999) prices are obtained through a restricted dual problem that mimics complementary slackness conditions, but item prices are not minimized. The primal complimentary conditions satisfaction and ensuring dual feasibility using an extra variable that is added to each constraint that corresponds to unallocated packages that bids were placed on. RAD prices do not hold when integral property holds.

iBundle (Parkes 2000a) is the first iterative combinatorial auction in literature. In the initial phase all the prices set to zero and in the bidder evaluation phase, given a current set of package prices each agent determines the set of packages that are within a bid increment of epsilon of maximizing utility. The winner determination is a primal allocation using the WDP to maximize his revenue. The pricing phase (dual pricing) determines the package prices and reported back to the bidders. The bidders evaluate the package prices and resubmit their bids. The basic assumption in iBundle is that the

bidders employ myopic best response where only utility maximizing packages are submitted.

2.2 FREIGHT SERVICE PROCUREMENT

Most of the literature related to optimization and the trucking industry focuses on routing and scheduling optimization models for carriers and does not explicitly address the processes involved in contractual agreements between shippers and carriers. However, in the general supply chain management literature, procurement between manufacturers and suppliers has been studied extensively.

Transportation and distribution are two key parts of supply chain processes. These processes incur significant costs and hence reducing these is a primary concern. Freight procurement (or sourcing) can be defined as the purchasing of contracts for transportation services. Procurement involves two different sets of entities: i) Shippers – who need a demand to be satisfied and ii) carriers – who provide transportation services. The primary entities involved in freight transportation supply chain processes are shippers (manufacturers, suppliers etc.) and carriers (third party logistics, less-than-truckload, truckload). In freight contracts, the shipper is the ‘manufacturer’ and the carrier is ‘supplier’.

Shippers are assumed to be rational agents who generate shipment demands with different attributes (Origin-destination pairs, commodity type, stock out costs, time-windows etc.)

Carriers are the agents who sell transportation services. Their business making decisions are dependent on current fleet status, load assignment strategies, pickup and delivery strategies, capacities, and demand characteristics. They want to maximize their profits or enhance their market power.

Freight transportation procurement involves negotiations among shippers and carriers for mutual advantage. In this freight procurement, shippers act first by forecasting their demands so that they can express their predicted needs to the carriers. Proper forecasting of their requirements is of primary importance in this process.

The other factors of shipment details are:

- Volumes and weights of shipments
- Origin/destination locations
- Level of service (LOS) details
- Add-on accessorial details
- Primary shipping locations for unforecasted demands
- Technology requirements
- Cost structure (freight rates)

Service levels can be characterized by: transit schedules, claims ratios, on time deliverables (time-windows) and penalties for failing to meet service levels.

According to the (Hubbard, 1998), the organizational forms of motor carriage can be differentiated into three categories.

Common Carriage is defined “as a carrier that held themselves out to the general public to perform the transportation and related services that were identified in their grant of authority.”

Contract Carriage is defined “as performing dedicated transportation services to separate shippers, in accordance with a required permit that was obtained from the same agencies described above.”

Private Carriage is defined as “performing transportation services in the furtherance of the primary business enterprise.” In these situations a shipper have their own fleet, drivers and operates them under the shipper’s full control (TransportGistics).

A contract is a document of freight service rates and quality of service levels mutually negotiated and deliberated by the shipper and the carrier. A “Bill of lading” contract is for a single shipment, used for short-term contracts and also acts as a receipt for shipment. “Contract carriage agreements” are used for creating long-term contracts involving multiple shipments and consignees. These agreements include specific delivery

schedules, equipment, claims details, freight rates, incidental transportation charges etc. In the transport sector, contracts extend for large periods usually one year and under the contracts can be revised regularly. Therefore, carriers want to maximize short-term profits, satisfy contractual obligations and also achieve profits over the long period. In the trucking industry a base rate per unit good transported between an origin-destination pair is set contractually and the carrier provides service for this base rate. If the shippers need more capacity, then the carrier may charge a spot price or may extend the contract price to additional demands. Most contracts require that a target amount of cargo should be transported at each period. The shipper has to meet the set target demand and the carriers assign capacity to satisfy the target demand. Failing to do so will mean penalties for the non-compliant party as specified in the contract agreement. Contracts may also address risk sharing. This may take different forms. A common one involves a menu of prices that apply to different demand realizations.

The sequential activities of freight procurement are as follows. Usually the shipper forecasts a demand and asks for capacity from the selected carrier. The carrier assigns a capacity W and the contract is signed. In the course of the period, a shipper observes a demand $Q(L)$ and assigns a portion U of it to carrier C . The carrier C observes the spot market and allocates capacity $X(L)$ to the shipper and capacity $X(S)$ to the spot market(s). After looking at the share allocated by the carrier, the shipper allocates the rest to the spot market. Then transportation is performed and payments are made.

Spot market contracts are relatively short term contracts to serve unfilled demands or demand surges (or contingencies). These have short lead times, volatile market prices and typically no prior contractual agreements. The payment mechanisms can involve shippers paying for one way or two-way transportation (which may include an empty backhaul). Common carriers usually operate in the spot markets. The spot market can be considered to be a ubiquitous market where the prices are determined by the market forces. Typically shippers and carriers participate in spot markets on a “per job” basis.

Shippers require long-term transportation infrastructure commitments and face stochastic demands and stochastic spot prices; they enter into long term contracts with carriers to minimize the spot market volatility after carefully selecting the core carriers to use for their business. Shippers draw up long-term contracts with several carriers for periodical quantity commitments, limited flexibility (the shipper can exceed contracted capacity per period by paying progressively higher prices), frequencies, transportation rates, quality of service and non-compliance penalties. The carriers also have contractual agreements with several shippers, which may lead to overbooking of their capacities. In addition to developing long-term contractual agreements, carriers tend to reserve some capacity for short-term spot markets. Contract terms are signed for a long period, typically one year. Shippers enter ex-ante long-term contracts but also have the ability to enter spot markets for unforecasted demands. The shipper might also do this because contracting for large capacities with carriers may prove uneconomical. A carrier signs a contract and also pools their excess capacity in the spot market to take advantage of the spot

market prices. For a long-term contract, the shipper constructs a set of target demands to be met for each origin-destination pair and invites pre-qualified carriers to bid. The shipper selects the carrier based on the amount of capacity the carrier can promise. In the second round the shipper's present their demand information, and a carrier is selected based on a best bid and the contract is drawn up. The left out carriers sometimes act as second tier carriers, and hope to get a part of the business from the shipper at spot market prices in cases of unforecasted or unfilled demands.

To ensure a win-win situation shippers and carriers must cooperate to share information and risk. Hence the drafting of the contract is of vital importance. However, the shippers and carriers may behave in an opportunistic manner. In freight transportation both shippers and carriers can be safely assumed to be risk averse. The most important information revelations are of course the exact capacity of the carrier and the exact demand of the shipper. Behavior is guided by the mutual benefits of cooperation among shippers and carriers, the value addition of doing business, and attitudes towards each other during the lifetime of the contract. Shippers can help carrier operations by decreasing the loading and unloading time, minimizing dwell time and providing advance shipment details. Some of the other information sharing avenues are: early or timely notification of transportation needs, subsequent changes in schedules, delays in delivery, type or quality of transport capacity available, price changes

In an auction based freight procurement the basic operations can be characterized for shippers and carriers as follows. Shippers have forecasted demands to satisfy using the spot markets and long-term contracts. The shipper can choose the classic auction schemes like first price or second price auctions or more complicated combinatorial auctions to select the carriers to for doing business.

2.3 TRUCK TRANSPORTATION MARKET

In this section we will look at the transportation market especially the trucking industry and motivate the use of auctions as a market clearing mechanism. The deregulation of interstate motor carriers in the 1980's (Motor carrier Act) and intrastate in early 1990's brought in a new era of competitive environment. Shippers and carriers adopted new technologies (GIS, ITS, JIT) to enable them improve their supply chain and transportation processes respectively. Innovate ways of procuring freight and a variety service structures came into existence. In this thesis we consider the trucking industry auctions and we present the characteristics of the trucking industry.

Trucks do not have the right of way and use public highways. Trucking cost structure rates are variable and pay for the usage of highways. Trucking industry can be classified into basic types based on the consolidation strategies, Truckload (TL) and the less than truckload (LTL). The trucking industry especially the truckload industry is much less

concentrated than the rail industry. Less than Truckload (LTL) actually has a few big players.

2.3.1 Truckload

Truckload (TL) operations are a direct linkage from an origin to a destination service. Large TL firms like Schneider, and J.B. Hunt strive for economies of scale, scope and have better fleet management, coordinated maintenance driver training etc. Typical operations for a large shipper are load screening that is whether they should take up a load for service and truck dispatching, trucks being assigned to loads. A review of pricing structure is periodically performed for the load screening considering level of competition and shipper relations.

Typical considerations for truckloads:

- Revenues from a load
- Costs of moving the load from origin to destination
- Potential of the destination to get a new load
- Empty repositioning (deadhead) for a new load from the destination or wait at the destination (dwell) for a new load

- Utilizing capacity by adding further loads being generated probabilistically over time and space with different revenue and cost characteristics
- Satisfy pre-contracted demands from core shippers

In literature, large truckers have developed models where they assign values for a truck at a particular point in the network. Fleet management problem is the problem assuring that the truckers are at the valuable nodes in the network. For a survey of research on these problems, refer to Jaillet and Odoni (1988), Powell, Jaillet and Odoni (1995) or to Bertsimas and Simchi-Levi (1996). TL market is a rough and tumble market with aggressive pricing, while being flexible and responsive. The operating ratio of truckload market is about 95%. In the US truckload market there are approximately around 50,000 TL firms and of these 40,000 are very small, with less than six tractors (Federal Motor Carrier Safety Administration, 2005).

2.3.2 Less than Truckload

LTL networks operate more like railroads and somewhat different from TL operations. They have terminal and a feeder network that picks trucks from small shippers in small trucks. They are brought to end of line terminals. They are aggregated, transported line-haul to other end-of-line terminals, at which point the reverse operations take place. The shipments are disaggregated and are typically distributed in smaller trucks. LTL carriers

are usually large firms because of the infrastructure requirements of their operations. In LTL market the large thirty-five firms account to about 85% of the market share, but the revenues from LTL sector is about one-third of TL sector (Federal Motor Carrier Safety Administration, 2005). Some of the large US firms are: Roadway Express, ABF Freight Systems.

2.3.3 Contract Structures

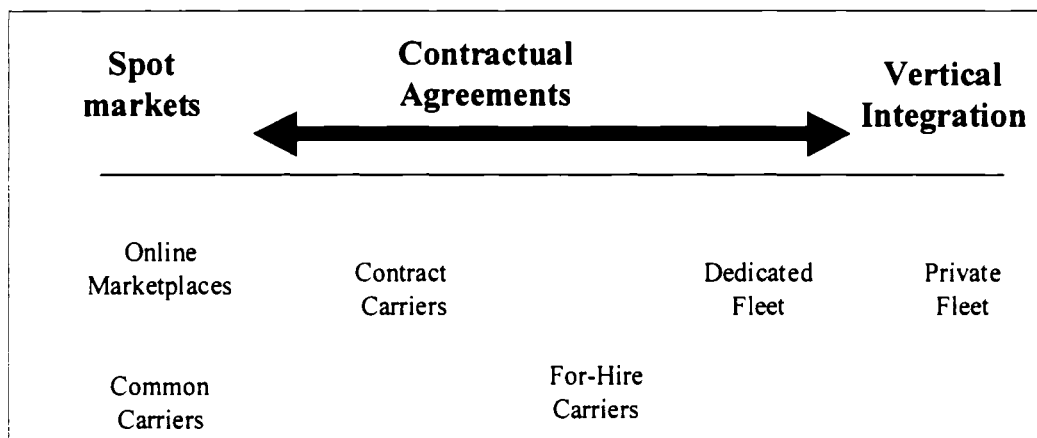


Figure 2.1 Contract structures in truckload market

As shown in the Figure 2.1, the truckload contract structure consists of three divisions: spot markets, long-term contracts and vertical integration (Hubbard, 1998). Common carriers operate in the spot markets and online marketplaces are increasingly being used to match shipper demand and carrier capacity. Shippers prefer long-term alliances with carriers and usually have a “core carrier” program, the select mix of carriers whom they do business with (Gibson, Mundy and Sink, 1995). The contractual agreements are formed with niche transportation for-hire carriers, who are paid by the shippers for hauling their goods. For-hire carriers get most of their revenues for providing

transportation service and/or related service like logistics management. Some shippers that manufacture and distribute goods have private fleets to transport goods to their customers. For-hire carriers usually allocate high percentage of capacities in the long-term markets.

Generally shippers have private carriers because they have to serve time sensitive demands in a timely and reliable manner to satisfy their or the their customer's supply chain practices. Dedicated carriers are for-hire carriers who replace a company's private fleet and completely dedicate vehicle capacity to a shipper. Shippers use dedicated carriers for JIT or highly time sensitive shipments, since vehicle capacity is of primary importance.

2.3.4 Auction Categorization Framework

Kalagnanam and Parkes (2004) have suggested a framework for classifying the auctions based on the requirements that need to be considered to set up an auction. Based upon their framework, we categorize transportation auctions in the following table.

Resources are items over which the auction is conducted (Single or multi items, standard or multi-attribute). In multi-attribute auctions we need to specify non-price attributes or utility scoring functions in order to trade-off these attributes. In a transportation auction, the items traded are shipment lanes (an origin-destination pair) or serving an entire zone or cargo capacity. The resources in transportation exhibit spatial temporal characteristics

along with different modal structures such as TL/LTL, Ocean, Rail, Air services and Inter-modal freight.

Table 2.1: Classification for Transportation auctions

Categories	Transportation auctions
Resources	<ul style="list-style-type: none"> • Lanes • Zones
Market Structure	<ul style="list-style-type: none"> • Forward auctions • Reverse auctions • Double auctions
Preference Structure	<ul style="list-style-type: none"> • Bidders utility functions
Bid Structure	<ul style="list-style-type: none"> • Single Lane unit • Multi lane units • Package Lane units
Matching supply to demand	<ul style="list-style-type: none"> • Single Sourcing • Multiple Sourcing
Information feedback	<ul style="list-style-type: none"> • Direct mechanisms • Indirect mechanisms

Market structure is determined by the nature of demand and supply. An auction is a negotiation mechanism, which matches buyers and sellers. In a forward auction a single seller sells resources to multiple buyers. In reverse auctions a single buyer attempts to source resources from multiple sellers. Reverse auctions are primarily used in transportation, where a shipper asks for bids from carriers to serve their demand. A

forward auction can be used, if the carrier asks for bids from the shippers for their cargo capacity. Auctions with multiple buyers and sellers are called double auctions and exchanges. The truckload market is a competitive market with few big players. The LTL market is an oligopolistic market with very large consolidated carriers. Sometimes if a carrier wins the right to serve (primary carrier) and is not able to commit their capacity, the carrier can contract it to another carrier or the shipper can ask a secondary carrier to satisfy his demand or the carrier can sub-contract the load to a different carrier.

Preference structure: it defines an agent's utility over different outcomes. It helps the shipper to design auctions such that the carrier who values the shipment most is allocated the lane. In carrier bidding the reservation prices for each shipment are random variables. The utility consists of two factors: strategic and operational. The strategic factor takes into consideration the profit margins charged by the carriers. The operational factors are influenced by the actual costs involved in providing the service for that shipment.

Bid structure: Bids can be single unit, multi-unit or package bids of lanes (or the entire region). Single unit bids need to specify a price. Multi-unit bids must specify a price and quantity. Packages are defined heterogeneous multiple items i.e. lanes in a transportation setting. Bid structures are also impacted by the commitment of the carriers, for example:

- Firm commitment at all times for the submitted bid
- Providing service for a bid within a given committed duration
- Flexible commitment on the bids

Matching supply to demand: This is referred to as market clearing or winner determination problem. The main decision for the shipper is to choose: single source-where a lane is awarded to a single carrier or multiple sourcing: where a particular lane volumes are assigned to different carriers.

Information feedback: In direct a mechanism there is no feedback such as price signals, from the auction. In an indirect mechanism agents adjust bids in response to the price signals and a provisional allocation. These mechanisms give rise to a range of questions related to the development of efficient information structures.

In a transportation auction, some of the information feedback structures are:

- Competitors' past bids
- Competitors' fleet status
- Number of competitors watching or bidding
- Shipment reservation prices
- Carriers structure: fleet and crew size
- Competitors fleet management strategies and bidding strategies
- Competitors' beliefs
- Information of resolved shipments during the process of the auction (provisional allocation)
- Information about shipper's business considerations

Valuation issues: This is the most important thing in most of freight carrier bidding. It also depends on the kind of information that the bidder has. Usually the valuation issues in auction theory (Krishna, 2003) are modeled by using either the independent private values model or common-value model.

In Independent private values model, each bidder knows precisely the valuation of the item, but does not know the valuation of others. She has a perception of other's valuation as drawn from a common valuation. This is called "common knowledge" in game theory parlance. The valuations of any pair of bidders are mutually independent. Under the common value model, the item has a single objective value but nobody knows its true value. If V is the item's true value, each bidder has a perceived different value $v(i)$ which is an independent draw from a conditional probability distribution $H(v(i)/V)$ and this distribution is common knowledge. In transportation auctions, calculating the valuations of the items involves solving complex network optimization problems, which will be discussed later.

2.4 TRUCKLOAD BIDDING ITEMS

From this point, we will focus on the truckload industry unless otherwise stated. In a transportation auction, the items being bid upon are the commitments to provide service.

Transportation service is multi-attribute in nature with the following characteristics:

- Location pairs (spatial structure)
- Volume (or frequency of service)
- LOS (on time performance, handling reliability etc.)
- Time windows, pick up and delivery constraints (temporal structure)
- Costs of service

In a transportation auction, bidding is done on a network, which consists of a set of interconnected lanes or zones (regions). A *location* is a title for one or more actual origin(s) or destination(s). A location could be a *point*, such as a single vendor, distribution center or store, or it could be a zone, such as a cluster of vendors or a cluster of stores. As before, a *lane* is a unique origin-destination pair requiring a specific type of service and equipment. Lanes can be point-to-point (e.g., vendor to DC), point-to-zone (e.g., DC to cluster of stores), zone-to-point (e.g., cluster of vendors to DC), or zone-to-zone (e.g., cluster of vendors to cluster of stores). In addition to its origin and destination, it is always better to specify for each lane the average route distance, average number of stops, demand forecast (truckloads), equipment requirements (e.g., dry van, flatbed, decked van) and service requirements (e.g., linehaul or linehaul to DC). Home Depot (Elmaghraby and Kescinocak, 2002) for example, actually provides the following information: i) origin and destination locations, ii) lane details, and iii) demand forecasts.

2.5 SPOT / LONG TERM AUCTIONS

The major considerations for freight transportation auction design are:

- Incentive compatibility. – Carriers have an incentive to hedge, or artificially increase, their bids based on uncertainty in the information provided to them.
- Interdependency due to economies of scope. – Bidding on each bid doesn't help to take into account the interdependency of the lanes, hence a combinatorial lane bids are necessary.
- System constraints. –Taking into account the shippers non-price business constraints.

The interdependency and the incentive problems can be reduced by careful design of the auction. Here a combinatorial auction is a nice procedure to achieve these objectives.

Following are the levels of planning in logistics applicable to freight procurement:

- Strategic – includes high budget infrastructure development: location of facilities, equipment procurement etc.
- Tactical level – includes transportation strategies including the frequency of which customers have to be visited. Transportation procurement for long-term contracts also falls in this level of planning. The contracts usually are for a quarter year to once every year.

- Operational level – day-to-day decisions as scheduling, routing and loading trucks. Transportation procurement using spot markets falls in this category.

For simplicity we define the two forms of contracting markets typically used in industrial freight procurement; long-term contracting and spot markets. Long-term contracts are for service that occurs over a period of a year or more. Large shippers prefer long-term contracts and form alliances with their core carriers. Spot markets are generally used to serve unfilled demands or underutilized capacity. Long-term contracts generally involve high strategic volumes, high investments from both the carrier and shipper, and need good shipper-carrier relationships. Spot markets usually imply lower volumes and no apparent relationships between the carrier and the shipper.

From the carrier's point of view, the problems involved in both the long-term contracts and spot term contracts are really different and depend on the service in question. The remainder of the paper assumes that a contract is made through an auction mechanism. We will define the auctions mechanism, auctioneer and the bidders as we go along. We first focus on the truckload carriers and then look into to LTL carriers auctions in spot markets. The procurement planning involves handling complex problems and hence it is useful to tackle the problem by defining using a framework-based approach. For this we resort to the dividing the problems based on a strategic, tactical and operational level from a logistics perspective.

2.5.1 Spot Freight Matching

In a carrier bidding problems, the decision to bid on the combinations of lanes to serve and the prices to charge is a strategic decision. The carriers' profits depend on the price parameters and fleet management (operational problem). The selection of the loads depends on the fleet management characteristics for the current and future time horizon. The evaluation process also has to take into consideration the kind of service in question (truckload, LTL etc.). The carriers are also involved in multilateral negotiations or multiple auctions or procuring using traditional means for the same transportation capacity. From a carrier's perspective, the yield management problem in electronic marketplaces is choosing the electronic auctions to participate in, setting the bid prices depending on the auction format and deciding how low they can bid. In multi-round auctions, the questions of interest would be the minimum bid increments and the bid stopping rules. The designed auction mechanisms will be helpful only if the mechanisms are Pareto efficient and equilibration occurs when these auctions are performed repeatedly. A holistic approach is needed, to design auction mechanisms and develop bidding strategies that will lead to some dynamic equilibrium in the auction games.

Freight-traders.com uses Vickery auction for their closed bid auction. We propose to use these classical auctions because of their easy of implementation and their widespread use in practice in current freight marketplaces. We discuss the issues in spot markets in detail in Chapter 3.

2.5.2 Long Term Contracting

Combinatorial auctions seem to be the preferred auction methodology in literature as well as practice. The development of optimal means for solving winner determination problems and for bidding is also important. For combinatorial auctions of lanes, both the winner determination problem (WDP) and the carrier's bidding problem are NP hard problems. Though small scale WDP's are solvable, many assumptions must be made. The biggest of these is that the demands offered by the shippers are known when in fact these can be highly stochastic. Similarly, the carriers assume that they can safely predict their future capacities – this too is an unreasonable assumption. In the future, sophisticated means to incorporate stochasticity in the offering, bidding and winner selection processes should be developed. These problems offer rich opportunities for researchers. In some cases the shipper must resort to using approximation algorithms to solve the WDP and ensuring fair allocations in such cases is very important. The development of iterative combinatorial auction mechanisms to reduce the burden of the shippers' allocation problems and the carriers' bid construction problems are an interesting topic of research.

In a transportation auction, the shipper usually designs the auction. In transportation auctions we do not deal with collusion, because the profit margins on every transaction is very low compared to other types of auctions, for example auctioning of mineral drilling rights. First and foremost, the items or lanes and their characteristics under auction must

to clear to the shipper. The choice of carriers to bid in these auctions is very important.

The following are the economic properties to be considered while designing auctions for long-term transportation procurement:

Economies of scale: It is defined as the decrease in marginal costs of serving a network if the volumes on all lanes increase in the same proportion.

Economies of scope: It is defined as the decrease in marginal costs by serving a set of lanes synergistic with each other.

Economies of density: It is defined as the decrease in marginal costs by increasing service to a zone or a customer location by keeping the total system traffic volume same.

In truckload procurement, economies of scope are an important property as it brings about synergies between lanes by reducing deadheading and dwell time costs. Caplice (1996) proposes the use of a combinatorial auction to take into account the economies of scope property inherent in truckload operations.

2.6 SCENARIO MANAGEMENT

The winner determination problem solves the allocation problem, but the final award might not concur with the non-price business constraints. In auctions this problem has been studied in Sandholm and Suri(2002), Kalagnanam and Parkes (2004). In the transportation auctions Caplice and Sheffi (2003) provide in details the non-price business constraints facing the shippers.

As discussed in Caplice and Sheffi (2003), shippers have a variety of business constraints when they assign bids to carriers. These include:

- Minimum / maximum number of winning carriers: a shipper could limit the size of carriers that can win in procurement auctions – at the lane, facility, or system wide levels. This is to control the risk of service unavailability and/or the overhead cost of too many carriers.
- Favoring of incumbents: shippers often favor particular incumbents in their core carrier group at the lane, facility or system level, or restrict particular carriers from serving certain portions of the network. Caplice and Sheffi (2003) noticed, “incumbents are often favored by 3% to 5% - especially on service-critical lanes to key customers or time-sensitive plants”. This constraint can be modeled by associating penalty cost for non-incumbent carriers.

- ❑ Back up concerns: a shipper may require carriers to submit both bids as a primary and backup service provider.
- ❑ Minimum / maximum coverage: a shipper may want to ensure the amount of traffic that a carrier wins within certain bounds, at a system, lane or facility level.
- ❑ Threshold volumes: a shipper can specify that if a carrier wins any freight (on a lane, from or to a facility, or system wide) that it is of either a certain minimum threshold amount, or they win nothing at all.
- ❑ Complete regional coverage: a shipper can require every carrier be able to cover all lanes from a certain location or in a particular region. This constraint can be addressed by combing all traffic from that location or region into a single package in the bid preparation stage.
- ❑ Restricting Carriers: certain carriers or groups of them are restricted from serving certain portions of the network. That means giving only certain percentage of the business.
- ❑ Performance factors: shippers may have a trade-off between cost and service.

It is imperative to take into account the above considerations to mitigate risk and also make decisions faster. A transportation procurement tool should be able to assess the impact of each business rule while awarding contracts to the carriers. The need for an optimization tool with plug-and-play capability to include various business scenarios is of utmost necessity.

2.7 MULTI-ROUND AUCTIONS

As mentioned in the above literature, transportation auctions exhibit both common and private valuations. Kwon et al (2005) consider a multi-round auction in a truckload market. Ledyard et al(1999) used a multi-round bidding in Sears logistics bidding mechanism. The shipper Home Depot conducted multi-round bidding for the right to serve lanes. Keskinocak (2003) reports that Home depot favored a single round because of the damaging price wars between the carriers.

Multi-round auctions have been defined above. The carriers may submit their bids in stages or all at once, and modify their bids at any time during the tendering period (or within each round, if the call for bids is multi-round). At the end of the period, all bids are collected and sent to an optimization system in order to determine, for each lane or each combination of lanes, the most advantageous set of bids.

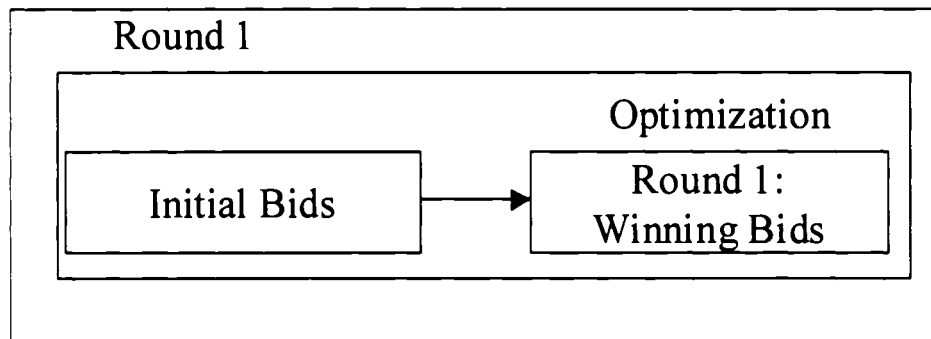


Figure 2.3 Single-round auction

If the online call for bids is single-round, the process ends with the awarding of

transportation lanes. However, if it is multi-round, the process is repeated for one or more supplementary rounds until termination of the call for bids. In this case, at each subsequent round, participants receive updated information on the state of the market, thus allowing them, if need be, to adjust their bids or change strategies. At the beginning of each new round, participants are usually informed of their leading bids and the value of the leading bid for every shipping lane. The number and frequency of rounds, the termination conditions, and various other rules, can all be implemented at the shipper's discretion.

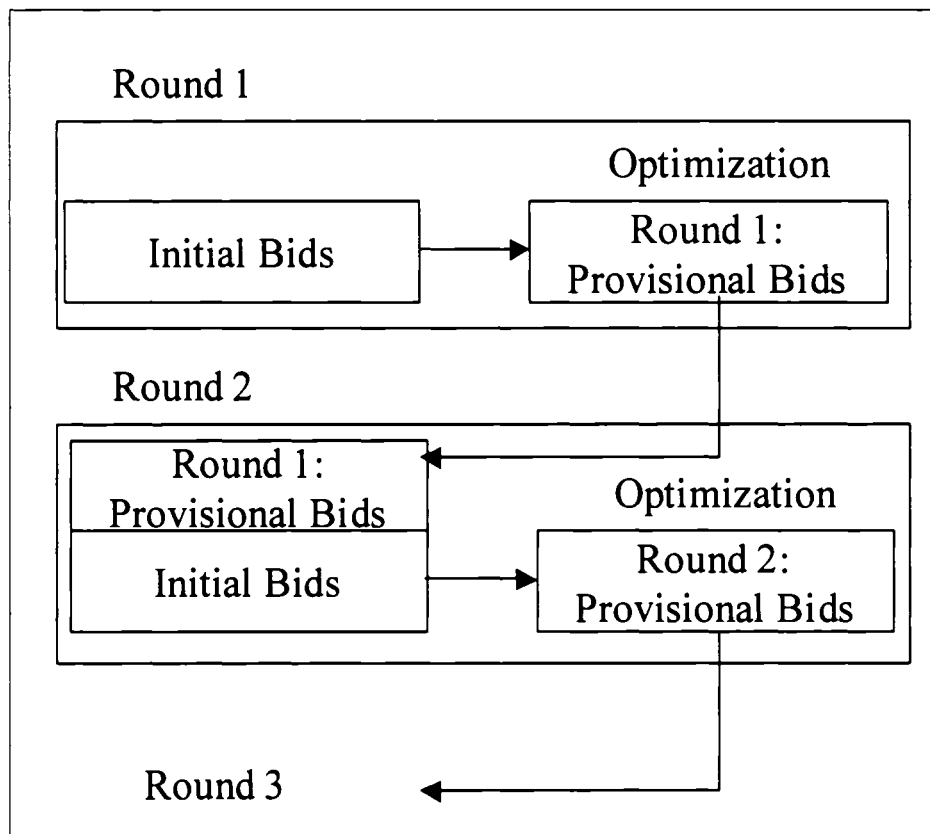


Figure 2.3 Multi-round auction

The disadvantages of one-shot auctions are that they are often sub-optimal. Some carriers end up with more business than they can handle while others lose valuable business because they misread the market. In both situations, the carriers are stuck for the contract duration and, as a result, the shipper may receive poor-quality service on some lanes while paying high prices on others. But transportation procurement is itself burdensome for even medium size bids involve thousands of independent items/products each with own quantity (Sheffi, 2004). Also there are business constraints too while awarding the lanes. Most of the shippers use only one shot closed auction because the whole process is cumbersome process as shipper networks are relatively very large.

CHAPTER 3 ELECTRONIC MARKETPLACES FOR AUCTION BASED TRANSPORTATION PROCUREMENT

In this chapter, we look at the use of auction mechanisms in existing electronic market places for spot markets in freight transportation procurement. E-commerce facilitates the reduction of supply chain intermediaries and reduces transaction costs. This revolution has spawned a number of online marketplaces for freight transportation service procurement. This chapter examines the business models of existing electronic freight marketplaces and the strategic behavior of shippers and carriers conducting their business in these market places. A brief literature survey of market clearing mechanisms models for online freight transportation marketplaces is presented and models for shipper-carrier strategic interaction are presented for freight transportation procurement. Some of the key research questions for developing methodologies to aid both the shippers and carriers will be discussed.

3.1 INTRODUCTION

E-commerce continues to be significant factor in the US economy and forecasts indicate the sector continues to grow. The US business-to-business (B2B) e-commerce market was \$823 billion in 2002 and is predicted to grow by \$2.4 trillion by the end of 2004 according to some market research firms (Standard and Poor's, 2003). E-procurement, the acquisition of goods and services over the Internet has evolved into an important

channel of procuring goods in the supply chain system. A reliable and efficient means of goods transportation is vital for the success of E-procurement. For business to consumer (B2C) e-commerce, express parcel services clearly dominate the market. However, B2B e-commerce relies more heavily on less-than-truckload and truckload trucking services. The trucking industry is heavily fragmented, fiercely competitive and operates on low profit margins. Hence it has historically been relatively slow to adopt technologies. Though the transportation industry has been slow to change, electronic freight intermediaries are beginning to emerge and to make inroads into this market. We should point out, that this is really the second entry of these players into the market. Several hundred such companies emerged between 1999 and 2001 but most of these quickly exited during the so-called dot com bust (Song and Regan, 2001).

The word “online” is synonymous with the Internet and a freight service company having an Internet presence enjoys significant benefits. It serves as a means of advertising, a way to reach new markets, and a way to communicate in real time with supply chain partners. Companies also are able to cut administrative costs as transactions are performed electronically and devote their time to enhancing customer service. In the express parcel industry, UPS, FEDEX and DHL for example, have been able leverage the power of online tools to serve their customers.

Online freight marketplaces are portals where transportation capacity is bought and sold. In the B2B jargon these can be categorized as vertical marketplaces as they deal with transportation specific and sometime other value-added services for transportation

management. The marketplaces offer short-term (spot market) and longer-term contracts. The electronic marketplaces can be broadly characterized into the following ways depending on the services they provide. The primary categories are:

- Clearing houses
- Auction houses
- Freight Exchanges

In an online clearinghouse, carriers and shippers post their requirements, and carriers post their unfilled /unutilized capacity. A clearinghouse usually consists of a database of loads (an origin destination pair and an associated time window for pickup or delivery) posted by the shippers or transportation capacity posted by carriers. The agents in these cases, shippers or carriers (or third party logistics providers (3PLs)) peruse the database and initiate negotiations with other players one-on-one. The access to these portals is mostly through the Internet but some sites are also accessible through wireless devices that share EDI and XML based data. Carriers can peruse the loads using the Internet and web enabled cellular phones or personal digital assistants (PDAs).

In transportation online spot auctions, the items being auctioned are either transportation capacity or transportation demands. The participants are typically shippers, carriers, 3PLs and other forwarding agents. In an exchange, shippers and carriers exchange demands for transportation services for promises to provide transportation capacity. In a transportation exchange, shippers post their demands, carriers their transportation capacity and the online marketplace performs the matchmaking at a competitive price. The exchanges also

contribute in the efficient handling of negotiations and the overseeing of the logistical processes of both the shipper and carriers (Song and Regan, 2001). The market places are characterized as public or private depending on whether all interested carriers can participate or if participation is limited to a select few. The road haulage orders are usually spot or short-term deals and long term (or binding contract).

Auction houses and freight exchange marketplaces employ a variety of negotiation capabilities. The capabilities vary with respect to the complexity of the technologies employed. IT complexities involved in these negotiations in decreasing order of complexity are automated online negotiations, manual online negotiations, and manual negotiation over the telephone or by fax. These marketplaces bring about a range of interesting mathematical problems related to the way these negotiations take place (Figliozzi, Mahmassani and Jaillet, 2003, Ihde 2004).

In the traditional means of procuring transportation service, shippers scout for carriers who can best fit their service criteria at an acceptable rate. Negotiations are held person-to-person between representatives of the shippers and carriers to generate mutually binding contracts. Historically, shippers typically locked up most of their known demands with contracted carriers and looked to spot markets for unforeseen transportation demand or demands that were not fulfilled, despite being under contract.

Online marketplaces offer some advantages over traditional marketplaces. They smooth the complex negotiation process and lower transaction costs. They may lower costs because traditional staff need no longer occupy time with transactional, or contractual negotiations with individual carriers. The shippers lower their freight bills and

carriers fill excess capacities. Online marketplaces reduce the complexity of decision making as the agents come together in a marketplace and sell their assets. Shippers and carriers get access to more business opportunities and geographical scope without incurring huge expenses on advertising. Online marketplaces are tools to gather large amounts of data, which can be used by pro-active agents to leverage and improve their service efficiency and lower costs (Goldsby and Eckert 2003). Most importantly they are just a click away from the pulse of the market – making current market clearing prices available in real-time. Despite the merits of online marketplaces some shippers shy away as the marketplaces usually do not assume responsibility for the actual movement of freight. They only try to match the shipper with the best carrier based on the shippers' criteria (the exception is of course 3PLs that own marketplaces or carriers who host private marketplaces). In neutral marketplaces the problem of monitoring the execution and performance of business entities is hard. Some shippers also believe that trust, vital for good relationships, is hard to build without person-to-person negotiations. Unless the marketplaces provide and circulate good, reliable information about the agents in their marketplace, it will be difficult to engender trust to trade and attain the critical mass necessary to make the marketplaces viable.

The purpose of this chapter is to look at the current state of online freight marketplaces and study the business models underlying them. We present a literature survey of the market clearing mechanisms from different scientific branches like economics, game theory and operations research and critique their applicability to the freight transportation industry. Our intention is to provide a snapshot of the research in this area. Finally we

present some bidding strategies for carriers in online spot auctions using auction theory as the basis.

3.2 CURRENT FREIGHT MARKETPLACES

Before the large-scale deregulation of the US for-hire transportation industry, supply chain firms traditionally viewed transportation as an exogenous entity because of government controlled rates. After deregulation, procuring transportation became a complex decision because the carriers were able to offer integrated services as they were driven by competition and a wide variety of firms entering into the market. The carriers became a marketing arm of the shipper and also an integral part of the shipper's logistics network (Stock 1988). This paved a way for the shipper to concentrate on its core competencies and to leverage the expertise of the carriers. Carriers benefited by gaining more access to a traffic base, increased stability of market share and opportunities to diversify into new services. Deregulation was positive for shipper-carrier relationships as it led to more co-ordination and cost effectiveness. The complexity of decisions and to desire to better utilize the core competencies led to the rapid rise of the third party logistics industry (Menon, McGinnis and Ackerman, 1998). 3PLs are firms performing the logistics functionality for the supply chain firms. Firms communicated using EDI but the Internet boom drastically changed the way companies operate and helped improve communication. The first successful exchanges, NTE and DAT, grew out of load posting services that began in the early 1990's using simpler technologies. At the same time as these original logistics e-commerce sites were developing, e-procurement in manufacturing industries was taking giant strides.

Online marketplaces proliferated in the mid 1990's in different configurations and catered to different modes of transportation. Airline and Ocean freight marketplaces like Go Cargo.com (ocean shipping) and Global freight exchange (GFX) came into existence. The major logistics software providers, 3PLs, truckload and LTL service providers plunged into the market with their own marketplaces. The economic boom also brought about many non-asset based companies into the market. Transplace.com, which was formed by six major truckload carriers, led by JB Hunt, and Transportation.com, backed by Yellow Freight, serve the highway market. Transplace.com also focuses on providing a portal through which shippers can tender truckload, LTL, and parcel shipments to carriers under contract. About 1,540 carriers work with Transplace.com. The portal, which reported \$700 million in revenue last year, charges shippers for services such as freight booking and transportation. Small package leaders UPS, FEDEX and DHL developed online marketplaces and also formed strategic alliances with other marketplaces.

As things progressed the picture for most of these types of companies was not rosy (those mentioned above are some of those the ones that survived, and even thrived). Most failed to obtain necessary market share or to identify profitable business models. They also failed to develop good relationships with shippers and carriers. Shippers who had long-term contracts with the carriers were wary that these marketplaces would strain their existing relationships. In a just in time (JIT) environment, shippers were more concerned with service parameters and most marketplaces acted as a matching place for loads but did not assume responsibility for the execution of the service. Shippers used online spot

markets for their urgent demands, but for time critical freight, contracted carriers were used. Carriers also looked down on these websites as they felt that the price competition would cut into their already lower margins. Due to these difficulties the vast majority of the original online marketplaces shut down and others changed their business models to become ASPs, logistics service providers or formed strategic alliances with other freight industry companies (Coia 2002).

The supply chain software vendors are beginning to include strategic transportation procurement tools in their products. Manugistics Group, Inc. acquired Digital Freight exchange in May 2002 in order to add an online bidding tool to its SRM suite. Invensys Software systems subsidiary, Caps Logistics is on its third release of its transportation procurement tool called BidPro. Schneider Logistics introduced their Combined value Auction (CVA) module in June 2002.

Collaborative models for shippers and carriers were also formed. These were formed by companies that frowned on the auctions, which they believed tended to increase price competition and treated the carriers as a commodity. The other main advantage of shipper collaboration is the control of inbound logistics. Elogex sets up collaborative networks, providing shippers with transportation management software and arranging to make shipments visible while in transit through Internet based interfaces. Nistevo's private exchange enables clients to automate their load tendering with a core group of carriers, thus eliminating paperwork and look for backhaul opportunities. Lean logistics combines the transportation needs of shippers in order to obtain economies of scale and scope to lower transportation cost.

The electronic marketplaces have started focusing on helping shippers and carriers automate their long-term contracts. Several companies have developed software tools to automate the development of contracts. (for example Logistics.com, now part of Manhattan Associates and Transplace). These companies are helping to run combinatorial or quasi combinatorial auctions for shippers. Internet-based transportation logistics marketplace Transplace and Associated Warehouse Inc. have announced a strategic alliance to provide integrated warehousing, fulfillment, transportation and logistics services. Eflatbed.com is an online marketplace mainly serving the metal industry has a large base of qualified, flatbed carriers.

3.3 CLASSIFICATION OF E-MARKETPLACES

In electronic transportation marketplaces with reverse auction capabilities, the shippers post RFQ and the carriers respond by competitively bidding to the load tenders. The exchanges offer a wide range of services, depending on the technology they employ. Shippers can submit their loads either in the public marketplace or a private marketplace. A private marketplace for a shipper consists of his contracted carriers or in-house carriers. In a public marketplace all approved carriers can participate in the exchange. Some online marketplaces usually have a certified base group of carriers. The reliability of the marketplace is increased if all the shippers and carriers have been certified and based on their service records and business credentials. The marketplaces can also be categorized depending on whether they assume responsibility in the overall logistical processes. A neutral marketplace is a place, which offers capabilities for the shippers and carriers to match their demands, and is not involved in the actual execution of the

agreements. The marketplaces also offer specific modal or inter-modal services. They can also be differentiated by the geographical scope of their operations.

In spot markets, shippers' post individual pieces of business (mostly speculative freight and urgent demands requirements) and carriers can bid and start the communication process with the shipper. Shippers sometimes post hypothetical loads to test the market and gauge the pricing system prevalent in the market. In long term contracting, the shippers enter into long-term contracts with the carriers based on forecasted demand profiles over the period of the contract.

Table 3.1 Electronic freight market classification

Mode	Air, Road(LTL, truckload), Rail, Intermodal
Contracting	Long term(network wide), Short term(spot, lane wise)
Transaction platforms	Pricing at market conditions, reverse auctions, exchanges (double auctions), negotiations (electronic or traditional)
Bias or Neutral	Bias is being partial to either carrier or the shipper. Neutrality means impartial freight matching
Trading Hubs	Trading in Private communities or public communities

The auctions come in many flavors that vary depending on the information available to

the various players. The shippers have the final say in the auction process and are not obliged to assign the contracts to the lowest bidder. In our presentation of the case studies, we simply point out how the companies differ from the general description provided in the last two paragraphs. Most of the information we provide was obtained from white papers presented on the companies web sites.

FreightMatrix is an online provider of transport management services (TMS) and a freight spot marketplace. Spot market freight matching is done using i2 technologies software called Transportation Bid Collaborator(TBC). TBC has built in proprietary heuristics and mixed integer programming based tools to analyze bids. Carriers build their private network and the turnkey software optimizes the network. TBC helps in factoring the probabilities of backhaul and asset utilization. Carriers analyze the shippers' requirements and their operational network and look for synergies. The bidding is dependant on the number of lanes, service levels and types, the number of carriers participating in the auctions, and number of rounds for bidding (single or multiple). The marketplace facilitates the creation of online trading communities in a neutral and anonymous environment. The shippers can create a private marketplace with core carriers or participate in the portal's public marketplace. FreightMatrix's spot matching pricing is internal and is deemed as fair. They also provide routines for network planning to minimize transportation costs while maintaining service levels and for transportation planning for strategic decisions on locations, inventory stock policies and distribution strategies.

Freight-traders, a UK based online marketplace, is a subsidiary of Mars Inc. a

multi-national company and operates in Europe. They provide services for online design and management of freight tenders. The marketplace has about 2250 shippers and carriers working with them. LeanLogistics provides transportation management services (TMS) for carriers and shippers with real time planning, execution and visibility. Transportation management services have capabilities to award contracts network based (long term contracts) and lane wise (spot contracts). Leanlogistics also provides value added services like CMM (continuous move management) which looks at the network and plans for continuous and closed loop moves.

Logistics.com offers services to all modes and combinatorial transportation service procurement software. They help the carriers with carrier management tools to identify consolidation, domiciling opportunities for drivers and lowering costs. Domiciling refers to the process of getting truckload drivers back to their homes after several weeks on the road. Nistevo facilitates shipper collaboration by consolidating loads into full truckloads. The collaboration can be extended to repositioning of trucks for future loads and warehouse management. Hosted software service that enables manufacturers, retailers, and carriers to plan, execute, and settle their inbound and outbound transportation demands. It has more than 1400 carriers in the network and supports all modes including intermodal freight. Nistevo software tools help create private, semi-private network, share capacity, reduce shipment cycle time and cost of other logistic handling, collaborative logistic network.

NTE provides software tools for private freight exchange and neutral auction houses for shippers. The software tools help the carriers to participate in the shipper's

freight exchange and auctions. NTE started in 1994 as a phone in service and moved to Internet in 1995. NTE offers transportation management services and also takes financial responsibility for the transactions between the carriers and shippers. It caters to nationwide truckload services.

SUMIT CVA portal offers a suite of logistical functions for shipment planning, carrier selection, rate negotiation and freight auditing. It also enables shippers and carriers to view the functioning of these supply chain processes at every stage. SUMIT CVA uses the NEX combined value trading framework developed at Caltech (Ledyard et. al 2002). CVA is a multi-round auction configuration with dynamic bid revisions and service lane combinations based on the shipper's requirements. SUMIT CVA allows the efficient matching of carrier capacity with shipper demands by allowing carriers to bid on bundles of lane combinations and grouping of loads that reflect the best use of their transportation network. The system has been used to process bids from around \$5 million to \$130 million, mainly in truckload and intermodal markets. Carriers are able to enter their rates, create packages and conditional bids, review service requirements and analyze bid results. (Cotrill 2003)

In early 2001, TransCore, a global B2B and business-to-government (B2G) transportation technology provider, acquired DAT Services and its e-marketplace, DATconexus, now renamed Transcore Exchange. A neutral marketplace, TransCore runs an indigenous public network of consists of 18,000 participants. DAT was one of the original load matching services and penetrated the truck stop market with a variety of services.

Transplace was formed in 2000 through the merger of existing logistics business units

of Covenant Transport, Inc., J.B. Hunt Transport Services, Inc., M.S. Carriers, Inc., Swift Transportation Co., U.S. Xpress Enterprises, Inc., and Werner Enterprises, Inc. Its formation was led by J.H. Hunt logistics. Transplace uses its trademarked Dense Network EfficiencySM (DNE) platform a combined network across hundreds of shippers, thousands of carriers and multiple modes to obtain collaboration among the different entities in this highly fragmented transportation industry. DNE has a core optimization engine for better matching and asset utilization. It has a base of more than 3000 carriers with freight transactions worth more than \$2 billion in 2002. Transplace also provides 3PL services, transportation management services, brokerage and carrier bid optimization services.

Our research examines the emerging marketplaces in the freight industry and tries to draw some light on the classic auction mechanisms and the competitive bidding aspects. Auctions are not the only pricing mechanism used in the spot market transportation procurement. Some of the other important market clearing mechanisms in online auctions are online negotiations and posted prices. An electronic marketplace setting the pricing must use algorithms, which are competitive and simulate the off-line market conditions. Pricing should be fair and take into considerations such as differentiated service packages, seasonality and volatility of demand / supply, and the underlying business rules and restrictions. Online marketplaces such as NTE, DigitalFreight and Transplace have their own pricing algorithms.

3.4 LITERATURE REVIEW

Song and Regan (2001) provided a broad overview of emerging freight transportation intermediaries. Figliozzi, Mahmassani and Jaillet (2002) provide a framework for transportation auction analysis. They tackle the carrier problem in these reverse auctions and mention about the dynamic, stochastic and the complexity of the problem. The analysis of the problem is at the heart of many different branches of science and all these connections are laid out in brief. Simulation of the auction marketplace with demands occurring with a Poisson distribution and under a Vickery second price auction method are performed and analyzed. The analysis looks takes a complex problem, but do not actually suggest a bidding framework for the carriers for use in real life situations.

Ihde (2004) presents a new auction mechanism “Dynamic Alliance auctions” for spot market matching. The mechanism uses a package wise bidding for spot markets. He proposes that for the carriers better capacity utilization is achieved by forming complementary trips and round trips. The author develops the mechanism for an auction mechanism in which the different shippers demands are collected, aggregated and suitable match to form complementary trips. The routes here consist of two lanes: one head-haul and a back haul lane. The matching of demands is done using an assignment problem. In this auction the main focus is how the revenue should be split among the shippers for the carrier. Analytical results are presented for the equilibrium division of freight payment to the carriers by the shippers and the range of efficiency of the auction. The author also presents the merits of the auctions with regard to collusion and

bidding aspect from the perspective of carriers. Based on SIPV principle they develop simple carrier bidding strategies. The author also proves Nash equilibrium principles in these auctions. Experimental evidence is provided based on the simulations done using the data from Daimler Chryslers virtual trucking enterprise “Fleetboard”.

Figliozzi et. al. (2004) compare the different dynamic truckload pickup and delivery problems in competitive environment using sequential auctions. Random demands are generated with pick up, delivery and hard time windows. For each of these the carriers compete in a second price auction. In this paper four fleet assignment strategies are tested. Basic methodology is the marginal cost of introducing the load into the carriers’ operational plan. If the cost is positive we can accept, otherwise reject it.

The four technologies are:

- Naive marginal cost of appending to the trucks already serving.
- Solving a single truck VRP by appending this load and bidding the lowest marginal cost. The number of VRP’s solved are equal to the number of trucks
- Solving a multi-truck multi-depot VRP based on current fleet status by adding the auctioning load to the pool of loads to be serviced.
- Solving a multi-truck multi-depot VRP using dynamic marginal costs. The carrier also has a probability distribution of the demands he might be serviced in the future and he calculates the dynamic marginal cost of taking up the load now and looking into the future as to how it will impact the costs.

For a single lane spot market auction, with these assumptions it falls straightly into the realm of auction theory processes. Results from auction theory are directly transferable, for this model. In a spot market the only thing that is of interest is the study of sequential auctions (Figliozzi, Mahmassani, Jaillet, 2002). In this the demand is generated using some stochastic process and the bidders bid on the lanes in these auctions. They use a Vickrey (1969) pricing so that the bidders' strategy is to bid truthfully. They don't provide the formulae for the profit of the shipper in long-run and also the profit of each carriers in the long run for participating in these auctions.

Bary Tan, Fikri Karaesmen, Semra Agrali (2005) analyze a logistic spot marketplace with sequential auctions taking place for the right to move a container from one point to another in the network. Shippers are arriving at the market using a known distribution and carriers bid to serve the shippers by bidding in a second price Vickrey auctions. It is the first paper in literature, which actually takes into account the queuing analysis to tackle the sequential auction problems arising in the transportation industry. The authors assume capacitated server with a limit on the number of shippers and carriers at any point of time in the logistic marketplace. Using queuing theory the authors develop analytical solutions to quantify the benefits of the shippers and the carriers in these auctions under asymptotic situations. The paper doesn't really account for how the carriers should tackle the problem strategically, but give some idea of future revenues in the long-term environment.

3.6 AUCTIONS IN SPOT MARKETS

Electronic marketplaces give rise to many interesting problems for transportation

researchers and transportation professionals. The examination of the applicability of various auction mechanisms in different transportation services (Truckload, LTL, rail etc.) is of significant interest. The auctions for transportation procurement are typically multi-unit and multi-attribute. Bidding languages help the carriers efficiently communicate their bids. The impact of bid semantics on the auction mechanisms and efficiency needs to be understood. Another important issue, for carriers bidding in spot markets is how to incorporate information about previous auctions into future behavior.

For both shippers and carriers, negotiations may be one-to-one or one-to-many. A trucking company dispatcher managing a large fleet may be simultaneously involved in a number of such negotiations to get the right price for his or her transportation capacity. Carrier operations thus evolve in a highly dynamic environment, where little is known with certainty regarding future demands, travel times, waiting delays at customer locations, and precise positions of loaded and empty vehicles at later moments in time. Service is tailored for each customer and the timely assignment of vehicles to profitable demands is of the utmost importance. The price is dependent not only on the complementary backhaul opportunities but also on the dynamic and temporal characteristics of the carriers' fleet. The onus now is to find a set of strategies that will help the carrier to get the best price for its services. This problem is similar to the yield or revenue management in airline operations.

In these negotiations, pricing of transportation service is of vital importance, but other attributes like service characteristics and good business relationships also come into play. In the online marketplace negotiations, the main problem of the carriers is to decide on

what loads to bid for and the price he has to charge for the loads. For pricing the load under consideration, the carriers need to calculate the marginal utility of the load to have an idea of the price for the transportation service (Figliozzi, Mahmassani and Jaillet, 2003).

From a shipper's perspective, in online spot markets the problem is relatively easy as they do not have to deal with auction design. The shippers predominantly the classic auctions on online spot markets are i) English auctions ii) Dutch auctions, iii) First price auctions iv) Second price Vickery auctions and v) Double auctions. Combinatorial auctions are those in which multiple items are put out to bid simultaneously and in which bidders can bid on combinations of these items. Combinatorial auctions are generally not used in spot markets because of the time complexity of winner allocation and valuation of complexity of forming combination of items. The only problem comes with the multi-attribute nature of transportation services, that can be differentiated on several non-price attributes such as quality, delivery date etc.

Carrier's problem is the hardest of all. Carrier fleet management is in itself complex and bidding in online marketplaces adds to this complexity. The dynamics involved in bidding strategies, negotiation and utilizing the information in bidding environments needs a deeper understanding to develop methodologies to aid the carriers. In a carrier bidding problems, the decision to bid on the combination of lanes to serve and the price to charge is a strategic decision. The carriers' profits depend on the price parameters and fleet management (operational problem). The selection of the loads to bid depends the fleet management characteristics for the current and future time horizon. The

evaluation process also has to take into consideration the kind of service in question (truck load, LTL etc.). The carriers are also involved multi-lateral negotiations or multiple auctions or procuring using traditional means for the same transportation capacity. From a carrier's perspective, the yield management problem in electronic marketplaces is choosing the electronic auctions to participate, setting the bid prices depending on the auction format and deciding how low they can bid. In multi-round auctions, the questions of interest would be the minimum bid increments and the bid stopping rules.

Game theoretic auction models consider the strategy based on a general function of their private information and try to obtain their Nash equilibrium. The game theorists a priori assume that all the bidders will have the same a priori i.e. a symmetric strategy. The incumbent carrier base has more information about shippers' behavior and his demand distribution. Transportation auctions are asymmetric nature because. The shipper has to deal with this asymmetric information among the carriers' and design allocation mechanisms based on these.

3.6 AUCTION MODELS

The basic models of auctions are private value auctions and common value auctions. In the private value model, each bidder knows his true valuation, but not other bidders' valuation (Vickery, 1961). In a pure common value model the true value is the same for each bidder but bidder's estimation of the value can differ.

3.6.1 Single Independent Private Values (SIPV)

- Single object for sale
- Bidders risk neutral
- Bidders valuation is *i.i.d* on some interval according to a continuous cumulative distribution function F . Each bidder knows his exact valuation.
- All N bidders have the same continuous cumulative distribution function F .
- Bidders know their realization but they do not know what other bidders valuation is, but do know that they have the same F . (F is common knowledge)
- Bidders are not restricted by budgetary constraints
- The item is not put up for resale.

In SIPV model, the descending auction is strategically similar to the first price sealed bid auction (Vickery, 1961). With the private values model, in an ascending auction, it is clearly a dominant strategy to stay in the bidding until the price reaches your value, that is, until you are indifferent between winning and not winning. In the second price sealed bid private value auction it is optimal for the bidder to report his true value, no matter what other players do. In fact “truth telling” is a dominant strategy (and leads to Nash Equilibrium). Hence an ascending auction is strategically similar to a second price sealed bid auction. This equivalence is called the “revenue equivalence principle” in auction literature.

Proposition 3.1: SIPV model is applicable to spot market freight matching and not for long term contracting.

In these models the situation is also called symmetric because all the bidders have a common probability distribution F . The model in general can be applied to spot markets. This is especially true for carriers that have satisfied a forward move to a destination and want a backhaul move back to the origin. The assumption that bidders are independent is typically strong, but valid as the business is cut throat and in economic terms close to perfect competition. The common probability distribution F is valid, as the direct cost of moving a load from between an origin-destination pair is similar across carriers. The independence assumption is safe as the valuation depends on the trucks forwarding destination and deadheading involved. The cost of providing backhaul services varies across carriers because of deadheading or waiting for the load or for a repositioning time. The only problem arises with applying this model is the symmetry assumption (market structure). The consequences for the shippers are that because of “revenue equivalence” the expected value of the winning price is the same across the first price open bid auction and the second price closed bid auction. For carriers in a second price closed bid auction, it is weakly dominant strategy to bid their true valuation.

The Single Independent Private Value Auction (SIPV) does not take into account the time constraints of the auction that might be critical, because of bid sniping, a common occurrence on eBay and Amazon auctions. Bid sniping is the practice of entering a time-constrained auction at the last minute, hoping to be the final bidder. This behavior has been observed in some spot markets for transportation services (Ihde, 2004).

In the contract markets, however the SIPV does not apply because of the inherent nature of transportation capacity dependence on forming complementary or round trips,

package bidding a more viable form of bidding (Caplice, Sheffi, 1996). Ihde, (2004) uses SIPV model for developing bidding strategies for bidding in dynamic alliance auctions and proves the existence of asymmetric Nash equilibria in special cases. He also develops analytically shippers' expected payoffs and proves that it is safe from collusion, bid sniping. Experimental results are also provided

3.6.2 Common Values Auctions (CVA)

In Common value auctions, all the bidders assign the same value but do not exactly know what the true value is. In these auctions, the *ex post* value is the same to all but is unknown to any particular bidder. In the common value models a key feature is the “winner’s curse”, that is, the winner generally ends up paying more than the actual value of the prize.

Proposition 3.2: CVA model applicable to long-term freight transportation procurement and can be used to model interdependencies for spot markets.

Long term contracting is a strategic decision and CVA assumption is not a bad assumption because the value of the contract is same to all the carriers. Exact valuation is hard to find due the inherent dynamism and uncertainty in demand, fleet management and other unforeseen events. Carriers valuation will be based on the information signal received to them depending on the strength of their prediction of future events. Ledyard et al. (2002) model the auction for Sears Logistics based on the common value paradigm.

3.6.3 Carrier Bidding in Spot Markets

In this section, we consider a situation where a shipper has some demands and puts on the auction space for getting service. The carrier's problem is to whether he/she can serve the demand, at what price and what priority. It not only involves demand forecasting on the part of the carrier to foresee this but also capacity forecasting.

Since there is no time to actually estimate what other carriers are doing strategically, the bidders are i.i.d. Carriers who have empty movements generally use spot markets and they are willing to serve a lane so that they can gain some profit. Carrier economics in spot markets is controlled by i) C : movement cost and ii) R : Revenue due to a loaded movement. In this model a lane has to be serviced from point A to point B for some shipper, who puts the lane for bidding purposes. In the auction, N bidders to participate and E is drawn from a common distribution F , which is common knowledge.

Notation:

Carriers' utility function: $U(s) = R - C$

Shipper utility function: $U(s) = -R$ (focusing on the costs only)

R : is determined by the auction payment scheme.

C : is stochastic variable depends on distribution F .

For the carrier the main question is to find the true valuation of the load. The valuation of the load is the marginal cost of accepting the load given the carriers pre-existing commitments. If the marginal costs of serving the lane are negative, it is not profitable to bid in the auction. The carrier will bid on the load if the marginal costs are positive

and within acceptable profitable margin range. To find the true valuation the bidder has to solve a dynamic vehicle routing problem (DVRP). Since these take place in real time there must be a way to quickly solve the problem. The DVRP and fleet management problems have been the subject of extensive research (Lu, 2002).

In this stylized model we assume that the carriers with empty backhauls or under-utilized capacity are participating in the auction. From proposition 3.1, an SIPV model can be directly applied and based on this model we develop carrier bidding strategies.

Some of the other strict assumptions for the model are:

- Probability density of winning prices is obtained from historical winning bid prices.
- Number of bidders are known
- The operating line-haul costs to serve a lane are also known.

Notation:

$F(x)$ - the density function obtained from the historical winning bid prices.

b - the bid for carrier say i

C - cost obtained by solving his vehicle routing problem.

Without loss of generality, we develop bidding strategies for one carrier as the model assumes symmetric carriers. For a carrier to win, the bid price b must be the lowest.

$$P(b) = \prod_{j \in N, j \neq i} \{1 - F_j(b)\} \quad (4)$$

The carrier has to solve the following problem.

$$\max P(b)(b - c) \quad (5)$$

We obtain the following results:

Proposition 3.3: In second price auctions, the symmetric equilibrium is to bid the true

valuation and the carrier payoff is $\pi(c) = \int_0^c yg(y)dy$.

Proposition 3.4: In first price auctions, the symmetric bidding strategy is given by

$$\beta(c) = \frac{1}{G(c)} \int_0^c yg(y)dy.$$

Proposition 3.5: In English price auctions, the symmetric equilibrium is to bid the true valuation.

Proposition 3.6: In Dutch price auctions, the symmetric equilibrium is to bid the true valuation.

3.7 CARRIER AUCTIONS IN SPOT MARKETS

In this section we talk about railroads, LTL, ocean carriers who have a capacity restriction on the amount weight/volume ratio they can fill up. Here the carrier is the auctioneer and the shippers are the bidders.

This kind of bidding is more useful for ocean-based carriers as they have large capacities. Sometimes yield management techniques are used in especially ocean carriers for filling up the capacity. It is interesting to see how a mixture of yield management which gives the reservation price for each time the auction is taking place and an auction based methodology might work.

Each bid has 3-tuple (W_j, V_j, p_j) , (W_j, V_j, p_j) , for a single ship, truck or a rail compartment for one lane or single capacity and modeled as a single shot auction. The carrier solves the following winner determination problem:

$$\begin{aligned} & \max \sum_j p_j x_j \\ & \text{s.t.} \\ & \sum_j W_j x_j \leq W, \quad \forall j \end{aligned} \tag{6}$$

$$\sum_j V_j x_j \leq V, \quad \forall j \tag{7}$$

$$x_j \in (0,1) \tag{8}$$

This problem is a double knapsack problem and the knapsack problem has been researched extensively. The shippers in these auctions have private value assumptions. Based on the theory of competitive equilibrium an incentive compatible auction can be designed using the Generalized Vickrey payments (Parkes and Kalagnanam, 2002).

CHAPTER 4 UNIT AUCTIONS

4.1 INTRODUCTION

In this chapter we present unit auctions; auction schemes designed to give shippers more control over the bundling of lanes and to reduce the complexity for carriers bidding in combinatorial auctions. Large shippers have deployed a variety of business-to-business auctions to procure transportation services from common carriers based on periodically renewed contracts (Caplice and Sheffi, 2003). The unit auction is especially useful for shippers with agile supply chain management practices where time and reliability of service is critical and suitable for dedicated carriers.

A package in a unit auction is defined as a set of heterogeneous lanes bundled together. These packages allow the shippers to have control over the transportation process and under certain circumstances may be preferable to full combinatorial auctions, both to shippers and carriers. The winner determination problem is of critical importance to shippers and determines which contracts are assigned to which carriers and at what prices. The winner determination in these auctions depends on the auction mechanism design and shippers' non-price business constraints. These problems, both from the shipper and carrier points of view, are computationally complex. In this chapter we consider the long-term contracting problem with a unit/multi-unit bid structure. The resources being auctioned are lanes, which are combined to form individual packages. This is different from a combinatorial auction in that the shippers and not the carriers construct the bid packages. In unit auctions, carriers bid to win the right to

serve multiple pre-defined packaged lanes. Without loss of generality, the packages can be viewed as consisting of a single lane. Another important consideration is matching supply with demand from a shipper's point of view and can be accomplished using two design frameworks: i) Single sourcing and, ii) Multiple sourcing. In single sourcing, the shipper chooses a single carrier to serve a package, and in multiple sourcing (split volumes) the shipper is willing to consider solutions that aggregate volumes on a package across multiple carriers.

Furthermore, shippers also often have to consider certain non-price business requirements when they analyze the bids (Caplice and Sheffi, 2003). The motivation for designing the unit auction mechanisms comes from real-world transportation problems encountered for procurement in which lanes with multiple units are put for auction without package bidding with explicit consideration of side constraints (CombineNet, 2005). A leading software vendor for market driven resource allocation, CombineNet Inc., states that real problems in transportation and logistics involve numerous side constraints. Hence, to tackle these problems good techniques are needed for optimal resource allocation (CombineNet, 2005). For instance, a shipper often has an approximate idea of the number of carriers they would like to have as partners and the maximum business volumes to be allocated to each winning carrier. These side constraints complicate the bid analysis problem.

We develop formulations incorporating the shipper business constraints, namely a minimum and maximum number of winning carriers, minimum and maximum business volumes and favoring of incumbents, as side constraints in integer-programming

models for both the single and multi-sourcing frameworks and examine math programming based heuristics to solve these problems. Lagrangian relaxation based algorithms are developed to solve the bid analysis problems and are compared with the commercial software CPLEX. Further, we will present greedy algorithms for these problems and provide numerical results to analyze the experimental behavior of these algorithms on sets of test problems. Finally, we conclude our work and discuss future research problems.

4.2 MOTIVATION

To date, most of the procurement auctions in the transportation industry have been implemented as unit or non-combinatorial auctions in which carriers are allowed to bid only for individual packages that are pre-defined by shippers – these packages are mutually exclusive and typically collectively exhaustive. This system bundling takes place a lot in procurement of materials and is called “lotting” (Elmaghraby, 2004). Several commercial companies have developed methods for “lotting”. Of note is the patent application by Freemarkets, now a part of Ariba (Freemarkets). In traditional auctions each single lane was put to bid, without focusing on the interdependencies of the freight network. Furthermore, if the auctioning of lanes takes place in a sequential manner than it takes a lot of time to complete the auction, because of the huge number of lanes. In auctioning of the lanes simultaneously, though times are decreased, the carrier complexity is increased because of bidding on a huge number of lanes at once and finding the right to get complementary lanes in the auction. This is called the ‘exposure problem’ faced by the carriers where they may end with lanes that are not profitable

unless combined with some other synergistic lanes (Pekec, Rothkopf, 2003). Hence a simultaneous auction is better suited to transportation auctions. A combinatorial auction design is able to alleviate this problem, but the complexity of bidding on combinations is still a daunting task (Pekec, Rothkopf, 2003).

Proposition 4.1: In unit auctions, shippers combining lanes with strong interdependencies provides "economies of scope" property.

Shippers understand their demand patterns and shipping patterns evolution and it is to their benefit if they can come up with an aggregation of lanes, which exhibit interdependencies. These aggregated lanes can be treated as one unit put to auction for bidding. As noted in Chapter 2, large shippers have dedicated carriers who also use the shippers' private fleets and their drivers. It is mutually beneficial for the shippers to develop interdependent packages and put them to auction for the dual purpose of good shipper-carrier relationships and as well as getting the service for a reduced price. By combining lanes, which exhibit strong interdependencies, the shipper is able to satisfy the economies of scope property and also reduce carrier evaluation complexity. Unit auctions and their hybrids have been used in practice. Ariba and Freight-traders report the use of bundling or lotting for transportation auctions. A combinatorial auction becomes a unit auction, if the carriers only bid on single lane volumes with no packages of lanes (CombineNet, 2006). While a unit auction is not as economically efficient for the carriers as combinatorial auctions in which carriers have the freedom to build their own packages and make conditional bids, it has some nice properties and dominates the current transportation service procurement market. In practice, there are many potential

advantages. First, the cognitive or computational strain placed on carriers and shippers is significantly reduced. Identifying efficient prices and developing good bids in complex auctions is no simple task. Second, it gives shippers more control over how lanes are grouped. Since only the shippers have reliable historical demand information, this may allow them to develop packages with less overall demand stochasticity than could the carriers. Such a reduction in stochasticity is beneficial to carriers who can rely on the income stream from such contracts as well as to shippers, who can count on reliable and timely service. Finally, carriers will often dedicate a sub-fleet to serve large shippers so they have no intention of leveraging existing contracts to make new ones more efficient.

Sometimes, unit auctions may not also be the best solution. Identifying packages is still a hard problem, but usually shippers outsource the auction process and are in much better position technologically to be able to handle package development than the carriers. The other questions for the shippers to consider are whether the right packages have been developed. The carriers might be forced to bid on packages, which might be incompatible with their service network because of domiciling constraints. Other difficulties still remain for the actual execution of these package bids.

Bid analysis and allocation can be a daunting task for shippers even in unit auctions. The first issue is problem size – a transportation procurement auction can involve thousands of lanes and hundreds of carriers (Caplice and Sheffi, 2003, Elmaghraby and Keskinocak, 2003). If shippers can assign contracts solely based on bid price, the bid analysis problem would still be simple – a sorting algorithm can solve the problem very quickly since there is no interrelationship between different bid packages. What really makes

it complicated is when sophisticated business rules are involved. For example, shippers may wish to select a limited number of carriers as their service providers due to the difficulty of managing too many accounts. And they may want to explicitly include carrier performance in the selection process, rather than viewing all pre-screened carriers as equal. As a result, shippers have to balance between prices; costs associated with managing multiple accounts and expected service levels. For this reason, several third party logistics companies are dedicated to developing decision support tools for transportation procurement auctions, for instance, the Transportation Bid Collaboration tool developed by i2 inc. and OptiBid developed by Manhattan Associates.

Caplice and Sheffi (2003) discussed the constraints found in transportation service procurement auctions and presented the general formulation for the bid analysis (carrier assignment) problem, which were presented in Chapter 2. Guo et al (2003) discusses how to incorporate some of the non-business constraints into their carrier assignment models in unit procurement auctions for transportation services. Their formulation is somewhat different from one presented in this chapter. In our formulation, the items to be assigned are packages. In theirs, the items are lanes and the business constraint considered is shipper preference for specific carriers (expressed as penalty costs for carriers that are not preferred.) These penalties are modeled as negotiation costs at points of transit in their formulation. The bid analysis problems were solved using meta-heuristics and experimental results are presented in their paper.

The fundamental problem at the bid analysis stage in unit transportation procurement auctions can be formulated as the following integer program:

BAP:

$$\min \sum_{j \in J, k \in K} c(x_{kj})$$

$$s.t. \sum_{k \in K} x_{kj} = 1 \quad \forall j \in J \quad (1)$$

$$\prod \quad (2)$$

$$x_{kj} \in (0,1) \quad (3)$$

where:

j : a bid package in set J which may or may not include multiple lanes

k : a bidding carrier in set K ;

$c(x_{kj})$: the shipper's cost to select carrier k to serve package j ;

x_{kj} : is a binary variable indicating whether a carrier k wins a package j ;

\prod : any business or logical constraints;

The objective function of the bid analysis problem BAP is to minimize a shipper's total costs to procure transportation services for a group of lanes in set L . Note that the cost function can be defined to incorporate non-price parameters such as service performance ratings in addition to prices. The first constraint ensures that each package is assigned to

one and only one carrier. The second constraint models specific business constraints defined by shippers.

Note that packages are mutually exclusive in a unit or non-combinatorial auction, that is, $j_1 \cap j_2 = \emptyset$. As a result, no lane will appear in more than one package. Further note that without the second constraint set, the bid analysis problem can be easily solved by sorting the bid price for each package and assigning a package to the bidder with the least price. However, when business constraints are incorporated, it becomes more intractable.

The complete incorporation of all possible business constraints requires building a sophisticated decision support system and is beyond the scope of our study. In the following, we focus on those constraints discussed in Caplice and Sheffi (2003). In particular, we clearly modeled these business requirements as side constraints in our model: maximum and minimum number of winning carriers, incumbent preference, maximum and minimum coverage, and performance factors. The service backup issue can be illustrated in the bid preparation stage by requiring each carrier to submit both primary and alternate bids and hence is not considered here. The complete regional coverage constraint can be addressed by combining all traffic lanes from that location or within that region into a single bid package at the bid preparation stage. For performance factors, some shippers conduct pre-screening activities on bidder's qualifications at the bid preparation stage to ensure minimum level of services (Ledyard et al, 2002); another way to model this constraint is to use an adjusted price instead of pure bid price for the cost function. Essentially, this allows the shipper to penalize carriers that have not been pre-screened without completely eliminating them from consideration.

Finally, we assume that the freight volume on each lane is not separable.

Notation:

i : index of a lane in set L ;

j : index of a bid package in set J which may include multiple lanes

k : index of a bidding carrier in set K ;

c_{kj} : shipper's cost to select carrier k to serve package j ;

f_{kj} : shipper's cost per unit volume to select carrier k to serve package j ;

p_k : penalty cost for carrier k to be selected as a winner, $p_k \geq 0$;

K_{\max} : maximum number of carriers to be selected as winners;

K_{\min} : minimum number of carriers to be selected as winners;

V_{kj} : volume bid by carrier k for package j ;

\hat{V}_{kj} : estimated volume package j ;

We also have the following decision variables:

x_{kj} : binary variable indicating whether a carrier k wins package j ;

y_k : binary variable indicating whether a carrier wins anything at all.

4.2.1 Single Sourcing Formulation

$$\min \sum_k \sum_j c_{kj} x_{kj}$$

s.t.

$$\sum_k x_{kj} = 1, \quad \forall j \quad (4)$$

$$x_{kj} \in Z^+ \quad (5)$$

In a single sourcing formulation, each package in unit auction is assigned to one carrier and is modeled as constraint (4). This formulation is easy to solve, as the formulation is similar to an assignment formulation.

4.2.2 Multiple Sourcing Formulation

In this formulation, carriers bid involves volumes of the package and the price per unit volume (quantity, price pair). The winner determination formulation is as follows:

$$\min \sum_k \sum_j c_{kj} x_{kj}$$

s.t.

$$\sum_k V_{kj} x_{kj} \geq V_j, \quad \forall j \quad (6)$$

$$x_{kj} \in Z^+ \quad (7)$$

Constraint (6) states that the volume estimate for each package is covered. The solution methodology involves decomposing per each package and solving a knapsack problem for each package. For an extensive literature review of knapsack problems, the reader is referred to Martello and Toth (1990).

4.3 WINNER DETERMINATION WITH MINIMUM-MAXIMUM CARRIERS

In this section, we discuss a single round closed unit/ multi-unit auction for long-term contracting purposes with a restriction on the number of carriers handling shipper's business. Sourcing decisions usually involve multiple criteria in selecting the carriers.

4.3.1 Single Sourcing Formulation

Winner determination problem with single sourcing:

WDP-SS:

$$\min \quad \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k$$

s.t.

$$\sum_k x_{kj} = 1, \quad \forall j \quad (8)$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (9)$$

$$x_{kj} \leq y_k, \quad \forall k, \forall j \quad (10)$$

$$y_k, x_{kj} \in (0,1) \tag{11}$$

The WDP-SS formulation models the bid analysis problem faced by the shippers in single sourcing auction mechanisms. The objective function of this formulation minimizes total procurement costs including the actual “bid” price and the penalty cost. The first constraint (8) ensures each package can only be assigned to one package modeling the single sourcing constraint. Constraint (9) limits the number of winners that shippers want to have in their core carrier base. Constraint (10) is the coupling constraint between x_{kj} and y_k . The decision variable y_k is used to model the incumbency constraint. The shipper takes into account the incumbency of the carrier by ascertaining a penalty p_k for each carrier. This penalty can also be used to model the performance levels of the carriers based on the history of the carriers’ service.

Another interpretation of the formulation is selecting K uncapacitated facilities such that all the customer demand is satisfied at J customer locations (Daskin, 1995). Each facility has a fixed set-up cost and only a certain number of facilities can be set up. The constraint (9) can also be interpreted as a budgetary constraint on cost of setting up the facilities.

About the bid prices for these packages: The shippers provide reservation prices for each package, defined as the maximum price they can pay for providing service to each shipment. In this auction mechanism, it is stipulated that all of the carriers who are in the shipper’s base (core) set must submit a bid price that is less or equal to the reservation

price. This is a reasonable assumption because the auction is for long-term contracting and in the truckload carrier market firms, especially at the national level, are essentially equivalent. In practice, if the carrier is not able to honor the demand using its own fleet it can sub-contract the demand to another carrier. It is also assumed that the truckload market is quite competitive and collusion is not expected from the core carrier base. These firms want to bid more competitively to take into account the economies of scale and scope presented by these packages and also the long-term business commitments represented by long-term contracts.

Lemma 4.1: WDP-SS is NP-Hard.

Proof: The WDP-SS without the inclusion of the constraint (9) reduces to an uncapacitated facility location problem which is NP-Hard (Krarup et. al., 1983).

4.3.2 Multiple Sourcing Formulation

In freight procurement a contract based on “if there is a demand then service would be matched”, the shippers might face problems when the carrier under contract is not able to service the load. In this case the shipper has to contract the load at spot market price or give it to a secondary carrier. In multiple sourcing, the shippers award a percentage of loads to different carriers and are not totally dependent on a single carrier or a spot market. In this case the shipper has alternative portfolios of carriers given by the percentages of volumes allocated to each carrier. The shipper’s manager decides which carrier to use based on the supply matching. The formulation helps the shippers to reduce backup concerns and have a secondary carrier at their disposal instead of finding one on a

spot market.

Winner determination with multiple sourcing (WDP-MS):

$$\min \sum_k \sum_j f_{kj} v_{kj} + \sum_k p_k y_k$$

s.t.

$$\sum_k v_{kj} = 1, \quad \forall j \quad (12)$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (13)$$

$$v_{kj} \leq y_k, \quad \forall k, \forall j \quad (14)$$

$$0 \leq v_{kj} \leq 1 \quad (15)$$

$$y_k \in (0,1) \quad (16)$$

where v_{kj} denotes the percentage of total volume assigned of lane j assigned to carrier k .

The solution for the formulation is integral and hence the final solution will be similar to that of the WDP-SS. We can model the multiple sourcing constraints by placing a constraint on the percentage of volume of loads that can be awarded to each carrier. This

enables us to place a constraint on the maximum business awarded to each carrier.

WDP-MS:

$$\min \quad \sum_k \sum_j f_{kj} v_{kj} + \sum_k p_k y_k$$

s.t.

$$\sum_k v_{kj} = 1, \quad \forall j \quad (17)$$

$$\sum_j v_{kj} \leq T_k^{\max} y_k, \quad \forall j \quad (18)$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (19)$$

$$v_{kj} \leq y_k, \quad \forall k, \forall j \quad (20)$$

$$0 \leq v_{kj} \leq 1 \quad (21)$$

$$y_k \in (0,1) \quad (22)$$

where

T_k^{\min} : the minimum percentage of business allocated to carrier k if he is in the winning allocation;

T_k^{\max} : the maximum percentage of business allocated to carrier k if he is in the winning allocation;

In this formulation, constraint (18) models the maximum business awarded to a carrier at the system level. In addition, the following constraint helps us to model the business constraint of minimum / maximum coverage constraint at the system level.

$$T_k^{\min} y_k \leq \sum_j v_{kj} \leq T_k^{\max} y_k, \quad \forall j \quad (23)$$

There might also be package specific constraints on the volume of lanes that can be allocated to each carrier to facilitate the min/max coverage at the package (or lane) level. Additional constraints help us to complete regional coverage by assigning a high cost to the cost packages by some carriers. The level of service parameters can also be reflected by increasing the costs for the packages for specific carriers based on their history of level of service parameters.

Lemma 4.2: WDP-MS is NP Hard.

Proof: The WDP-MS without the inclusion of the constraint (13) reduces to a capacitated fixed charge facility location problem which is NP-Hard (Krarup et. al., 1983).

In the next section we provide a Lagrangian relaxation based algorithm to solve the WDP-SS and WDP-MS problems.

4.3.3 Lagrangian Relaxation Approach

The Lagrangian relaxation method employed is based on the works of Held,

Wolfe and Crowder (1974) and Fisher (1981). The Lagrangian relaxation algorithm is generalized as follows: first, given a specific μ_i , we find an optimal solution for the Lagrangian dual problem. Then we search for a feasible solution for the original bid analysis problem from this optimal solution; next we examine whether the stopping rule is satisfied, if not, we update μ_i and continue this procedure to improve the lower bound. If the upper and lower bounds do not converge, we resort to a branch and bound scheme to find the optimal solution.

Lagrangian Relaxation for WDP-SS

The choice of constraints to relax depends on the complicating constraints in the formulation. The next step is to decide which relaxation to apply. This decision is made based on finding one or more formulations, which satisfy the integrality property (IP). If the solution to the Lagrangian dual is unchanged when the integrality constraints are relaxed then the Lagrangian dual has the integrality property. The consequence of the integrality property is that the maximum lower bound attainable by the Lagrangian dual is equal to the lower bound achieved by the linear programming solution. Hence in general we try to relax the constraints that do not result in a Lagrangian dual with this property.

Relax constraint (12)

The problem structure makes it natural to consider relaxing constraint (12) in the WDP-SS formulation. This is because constraint (12) increases the complexity of the problem

immensely. Letting $\mu_j \in R$ be the Lagrangian multipliers, we have:

WDP-LR:

$$\begin{aligned} \max_{\lambda, \mu} \min_{x, y} \quad & \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k + \sum_j \mu_j \{ \sum_k x_{kj} - 1 \} \\ & = \sum_k \sum_j \tilde{c}_{kj} x_{kj} + \sum_k p_k y_k - \sum_j \mu_j \end{aligned}$$

s.t.

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (24)$$

$$x_{kj} \leq y_k, \quad \forall k, \forall j \quad (25)$$

$$y_k, x_{kj} \in (0, 1) \quad (26)$$

where $\tilde{c}_{kj} = c_{kj} + \mu_j$, note \tilde{c}_{kj} can be any real number.

Lemma 4.3: WDP-LR exhibits integrality property.

Proof: WDP-LR decomposes into the following formulation for each carrier say k_1 .

$$\begin{aligned} \min_{x, y} \quad & \sum_j \tilde{c}_{k_1 j} x_{k_1 j} \\ \text{s.t.} \quad & \\ & x_{k_1 j} \in (0, 1) \quad \forall j = k_1 \quad (27) \end{aligned}$$

These sub-problems have the integrality property since the linear programming (LP) relaxation of decomposed problems has integral solutions. The Lagrangian relaxation (LR) scheme hence in this case yields a same bound than the LP bound. But the interesting feature is finding a solution to the Lagrangian dual of WDP-LR is relatively simple to finding a LP bound, which will be presented in the next section.

Optimal solution for a relaxed Lagrangian problem

To solve this relaxed problem, suppose for each carrier we can find a list of packages J_k^* such that $\sum_j \tilde{c}_{kj} x_{kj}$ can be minimized, then we compute $p_k + \sum_j \{\tilde{c}_{kj} \mid j \in J_k^*\}$ for each k and then add these to a list. Then we select K_{\min} number of carriers from the decreasing order of the list. If there are still carriers remaining on that list such that $p_k + \sum_j \{\tilde{c}_{kj} \mid j \in J_k^*\} < 0$, then we continue adding those carriers as long as the constraint $\sum_k y_k \leq K_{\max}$ is satisfied.

To find packages in J_k^* , if $\tilde{c}_{kj} \leq 0$, we add package j into J_k^* for each carrier. For x_{kj} , we set $x_{kj} = 1$ only for those packages that are already picked by carriers in the last step, i.e., $x_{kj} = 1, \forall j \in J_k^*$. The Lagrangian dual provides a lower bound to the problem and the computational complexity for finding feasible Lagrangian solution is $O(\text{sort}(|K|))$.

1. Analytically, the Lagrangian optimal values for x_{kj} and y_k , can be found as follows:

2. For each carrier k , compute $V_k = p_k + \sum_j \min(0, c_{kj} + \mu_j)$, associated with selecting a carrier in the final allocation.

3. Sort the V_k and select the first K_{\min} and set $y_k = 1$. If $V_k < 0$ in the sorted vector set $y_k = 1$ until $|K_{OPT}| \leq K_{\max}$

4. Set

$$x_{kj} = \begin{cases} 1 & \text{if } y_k = 1 \text{ and } c_{kj} + \mu_j < 0 \\ 0 & \text{if not} \end{cases}$$

Solving the Lagrangian dual problem using this procedure will provide a lower bound on the objective function of the multi-unit bid analysis problem. Note that an optimal solution for WDP-LR can be infeasible to WDP-SS problem where some x_{kj} may violate constraint (1) – $\sum_k x_{kj} = 1$. Specifically, there are two possible infeasible solutions:

1. A lane is not covered, that is, $\sum_k x_{kj} = 0$;

2. A lane is covered by more than one carrier, $\sum_k x_{kj} \geq 2$;

In the next section we show how to construct a feasible solution using the Lagrangian dual solution.

Feasible solution for WDP-SS (Primal heuristic)

To obtain the feasible solution, using the Lagrangian dual optimal solution carrier set K_{OPT} , we solve the following problem:

WDP-FP:

$$\min_{x,y} \quad \sum_k \sum_j \tilde{c}_{kj} x_{kj}$$

s.t.

$$\sum_{k \in k_{OPT}} x_{kj} = 1, \quad \forall j \tag{28}$$

$$x_{kj} \in (0,1) \quad \forall k \in k_{OPT} \tag{29}$$

We present an outline of a simple greedy algorithm used to find the upper bound during the course of Lagrangian relaxation. The algorithm works as a primal heuristic in a Lagrangian relaxation as at every iteration c_{kj}^{\dagger} and Lagrangian multipliers μ are the input for this procedure to generate a feasible solution.

We start by simply assigning packages j to the nearest carrier k^* such that, $k^* = k^* | c_{k^*,j} \leq c_{kj}, \forall k \in OPT$, where OPT is the optimal Lagrangian relaxation solution. Since we assumed that every carrier bids for every package hence OPT will contain a minimum cost carriers bids for these lanes even though at the reservation price. Let the new carriers assigned be the set $K1$. In this assignment it might happen that the carriers allocated may be less than K_{min} i.e. $|K1| \leq K_{min}$. In this case we find the

minimum cost packages for all the carriers in OPT . Next we sort in descending order, the carriers in $OPT \setminus K1$ based on the minimum cost package and their penalty cost. We select from this list the first $K_{\min} - |K1|$ carriers.

Note that this heuristic does not give the best local optima in the neighborhood of the Lagrangian solution. In this methodology, we just want to see if we can generate a good feasible solution and see how it works with the Lagrangian heuristic scheme.

Lagrangian Relaxation for WDP-MS

Given two Lagrangian multipliers $\lambda_k \geq 0$ and $\mu_k \geq 0$, the Lagrangian relaxation formulation for WDP-MS is the following:

WDP-LR2:

$$\begin{aligned} \max_{\lambda, \mu} \min_{x, y} \quad & \sum_k \sum_j f_{kj} v_{kj} + \sum_k p_k y_k + \sum_k \lambda_k (\sum_j v_{kj} - T_{\max}^k y_k) + \sum_k \mu_k (T_{\min}^k y_k - \sum_j v_{kj}) \\ & = \sum_k \sum_j (f_{kj} + \lambda_k - \mu_k) v_{kj} + \sum_k (p_k - \lambda_k T_{\max}^k + \mu_k T_{\min}^k) y_k \\ \text{s.t.} \end{aligned}$$

$$\sum_k v_{kj} = 1, \quad \forall j \in L \quad (30)$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (31)$$

$$v_{kj} \leq y_k, \quad \forall k, \forall j \quad (32)$$

$$0 \leq v_{kj} \leq 1, \quad \forall k, \forall j \quad (33)$$

$$y_k \in (0,1) \tag{34}$$

Lemma 4.4: The Lagrangian relaxation to the WDP-MS with maximum coverage constraints and minimum threshold volumes can be solved using the WDP-SS.

Proof: From the above formulation WDP-LR2, it can be clearly seen that using the WDP-SS formulation can solve the Lagrangian dual of the WDP-MS Lagrangian relaxation. This relaxation is similar to WDP-SS in most ways as there is no restriction on the amount of business being awarded to a carrier; a carrier who is in the winning allocation will be assigned the total volumes of the packages with the nearest cost. The solution we get from this problem in each iteration step will not satisfy the constraint (30). Using this solution the feasible solution to get the upper bound for this problem can be found by solving the following formulation.

The problem we have to solve to get a feasible solution is

WDP-FP1:

$$\begin{aligned} \min \quad & \sum_{k \in K_{OPT}} \sum_J f_{kj} v_{kj} \\ \text{s.t.} \quad & \\ & \sum_k v_{kj} = 1, \quad \forall j \end{aligned} \tag{35}$$

$$\sum_j v_{kj} \leq T_k^{\max}, \quad \forall k \in K_{OPT} \quad (36)$$

$$0 \leq v_{kj} \leq 1 \quad \forall k \in K_{OPT}, \forall j \quad (37)$$

$$y_k \in (0,1) \quad \forall k \in K_{OPT}, \forall j \quad (38)$$

The above formulation takes the form of the classical transportation problem with lower bounds solvable in polynomial time. Hence this problem can be solved using the WDP-SS formulation. Thus it makes it easy for us to just focus on how to solve the unit-contracting problem and provide heuristics that will be helpful to solve the WDP-MS in the process.

To summarize, the procedure for Lagrangian relaxation based approach for WDP-MS the following:

1. Relax constraint (30), start from $u = u_0$, solve a relaxed Lagrangian problem WDP-LR2 to optimality using the WDP-SS formulation;
2. Find a feasible solution for the original WDP-MS problem from the optimal solution of WDP-LR2 by solving the formulation WDP-FP1;
3. Check whether any stop rule is satisfied, if not, go to the next step, else stop the program. Common stop rules include whether the lower bound is close to the upper bound and whether there have been too many iterations;

4. Update Lagrangian multipliers u with the Subgradient method and go back to step 1.

4.3.4 Subgradient Optimization

The feasible solution obtained with this procedure provides an upper bound for the original bid analysis problem, and we can further improve the lower bound solution by iterating the above Lagrangian procedures while updating the Lagrangian multipliers. There are alternative ways to do this; among them is the well-known subgradient search method (Fisher, 1981). Let $Z_n(\mu^n)$ be the optimal solution from the Lagrangian problem WDP-LR (lower bound) and x^n, y^n be the optimal assignment at iteration step n , and let Z_n^* be the feasible solution (upper bound), the subgradient search method starts with an initial value μ^0 for the Lagrangian multipliers and updates iteratively in the following way:

$$\mu_j^{n+1} = \mu_j^n + t_n (\sum_k x_{kj}^n - 1) \quad (39)$$

where

$$t_n = \frac{\lambda_n (Z_n^* - Z_n(\mu^n))}{\sum_j (\sum_k x_{kj}^n - 1)^2} \quad (40)$$

In the above equation, λ_n is a scalar satisfying $0 < \lambda_n \leq 2$, normally we have $\lambda_0 = 2$ and it will be halved whenever $Z_n(\mu^n)$ has failed to increase in a fixed number of iterations (Fisher, 1981). The iterative search for optimal solutions will stop when certain

rules are satisfied. These rules normally include: optimal or near-optimal solution is found; there are too many iterations; the scalar λ_n is too small.

4.3.5 Empirical Benchmarking

In this section we give some empirical results in order to compare the new approach to optimal winner determination based on the integer programming formulation of the bid analysis problem (and consequently solved with commercial software CPLEX).

Other input data for each problem includes each carrier's bids, bid prices, penalty cost, minimum and maximum number of lanes if this carrier is a winner, minimum and maximum number of winners. In our experiments, a carrier's bid price c_{kj} has a random profit component r distributed between (0,1) and a deterministic component based on distance distributed between 50 and 100. The deterministic component for each package is same for all carriers in the experimental setup. The penalty cost is randomly distributed between 0 and 3% of the total bid prices for each carrier. We set K_{\min}, K_{\max} to be randomly generated from the intervals $[1, 0.33 * |K|]$ and $[0.75 * |K|, |K|]$ respectively.

In practice a transportation procurement auction involves a dozen to several hundreds of carriers and a few hundred to ten thousands of lanes (Caplice and Sheffi, 2003, CombineNet Inc., 2005). In our investigation to test the computational efficiency of the solution procedure, we generate test suites including a set of small problems (20 to 50 carriers and 100 to 1000 lanes) and another set of large problems (100 to 500 carriers and 2000 to 10000 lanes). The numerical results are summarized in Table 4.1 and Table 4.2.

The lower bound in numerical results is the best lower bound obtained by solving the Lagrangian dual of WDP. The upper bound is found using the greedy algorithm presented above. Table 4.1 also lists the optimal solution and time by commercial software CPLEX. All experiments conducted on an AMD Athlon 1200 machine with 512 MB memory. For each type of problem, we tested about a dozen instances and the results are presented as the average over those instances. The computation times presented in the tables are in CPU seconds.

Further, the following rules are deployed to determine whether we should stop the iterations of Lagrangian relaxation based method:

1. Optimal solution is found (optimal solutions for Lagrangian problem are also feasible to the original problem, or the best upper bound is equal to the best lower bound);
2. Near optimal solution is found (upper bound – lower bound < 0.001);
3. The total number of iterations was limited to 100 for the small instances and 500 for the large instances;

$$GAP = (Z^U - Z^L) * 100 / Z^L \quad (41)$$

where

Z^U : Upper bound of the Lagrangian heuristic

Z^L : Lower bound of the Lagrangian heuristic

Z^* : Optimal solution using CPLEX MIP solver

The duality gap between lower bound and upper bound solution given by Lagrangian based method is very tight and the ratio between them is less than 5% in all cases; in addition, the Lagrangian feasible solution is also very close to the optimal solution.

Table 4.1. Average Solution Quality of Small Instances

Case Index	1	2	3	4	5
Number of carriers	[10,20]	[20,40]	[20,40]	[25,50]	[25,50]
Number of lanes	[100,200]	[200,400]	[400,600]	[600,800]	[800,1000]
Z^U/Z^*	1.000	1.000	1.000	1.003	1.001
GAP (%)	0.31	0.39	1.01	1.28	0.56
CPLEX time (sec)	3.00	7.00	16.00	31.25	35.50
Lagrangian time (sec)	1.75	3.75	6.75	10.50	11.50

Table 4.2 lists only near-optimal solution by the Lagrangian heuristic algorithms for large sized problems. In the large instances, CPLEX solved only instances of Case 1 and took 48 minutes on the average to solve the problem. The optimum solution from CPLEX was same as the upper bound solution obtained from the Lagrangian heuristic. CPLEX was unable to find a solution even after 4 hours for the rest of the large instances.

Table 4.2 Average Solution Quality for Large Instances

Case Index	1	2	3	4
Number of carriers	[100, 150]	[200, 300]	[200, 300]	[400, 500]
Number of lanes	[2000, 4000]	[4000, 6000]	[6000, 8000]	[8000, 10000]
GAP (%)	2.21	4.30	4.10	3.60
Lagrangian time (min)	2	6	8	14

In summary, the Lagrangian based heuristics have a clear advantage over exact algorithms. The latter cannot be guaranteed to solve practical bid analysis problems. Further, the Lagrangian based algorithm can provide solutions very close to optimal. The Lagrangian heuristic's performance was tested over 100 randomly generated test instances and is also very competitive computationally compared to CPLEX. In case of very large test instances usually encountered in transportation procurement, the heuristic was able to generate solutions efficiently with duality gaps within 6%, outperforming CPLEX.

4.4 WINNER DETERMINATION WITH COVERAGE CONSTRAINTS

Song, Regan and Nandiraju (2005) also develop carrier assignment formulations in unit procurement auctions (shippers determines packages), incorporating some of the above side constraints in the auctions in which the items are to assigned are packages of lanes. In that paper a single contracting auction mechanism incorporating the coverage constraints based on the total lanes awarded to each carrier at a system level is considered.

Now the bid analysis problem with shipper's business constraints and penalty costs in unit auctions can be written as follows:

(BAP-P)

$$\min \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k$$

s.t.

$$\sum_k x_{kj} = 1, \quad \forall j \in J \quad (42)$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max}, \quad (43)$$

$$T_{\min}^k y_k \leq \sum_j x_{kj} \leq T_{\max}^k y_k, \quad \forall k \in K \quad (44)$$

$$y_k, x_{kj} \in (0, 1) \quad (45)$$

In this model we also have $T_{\max}^k \geq T_{\min}^k \geq 1$ and $K_{\max} > K_{\min} \geq 1$. In addition to x_{kj} , we have another decision variable y_k – a binary variable indicating whether a carrier is a winner or not;

The objective function of the BAP-P problem minimizes total procurement costs including the bid prices and the penalty costs to manage multiple carrier accounts. As shown in Figure 4.1, there is actually a trade-off between these two costs: a very large carrier base will reduce bid prices, i.e., the actual transportation costs; however, contracting with too many carriers will increase shipper's overhead costs.

Further, note that a penalty cost can also be used to capture the shipper's favoring of specific carriers at the system level – incumbents have a zero penalty cost and non-incumbents have a positive penalty cost. The first constraint in the BAP-P formulation ensures that each package (lane) is served by one and only one carrier. The second constraint restricts the number of winners (size of carrier base) across the system in the final assignment. Constraint set (44) indicates the minimum and maximum coverage for each winner. That is, shippers want to make sure that a carrier carries a minimum and/or maximum amount of traffic volumes if this carrier is selected as a winner ($y_k = 1$). Though we only model this constraint at the system level, it can be easily modified to express restrictions at facility level. Also note that T_{\max}^k can be used to model a carrier's capacity. For example, a small carrier may bid for more than it can handle.

Constraint (44) is also a coupling constraint which models the following relationship between decision variables x_{kj} and y_k :

$$y_k = \begin{cases} 1, & \text{if and only if } \sum_j x_{kj} \geq 1 \\ 0, & \text{otherwise} \end{cases} \quad (46)$$

Next we analyze the complexity of this problem by transforming it to a Capacitated Fixed Charge Facility Location Problem (CFCFLP). The CFCFLP problem finds the number and location of facilities to serve a set of demand nodes while minimizing the sum of fixed facility location costs and the transportation costs between facilities and demand nodes (see for example Daskin, 1995).

First note that if we add another coupling constraint to the BAP-P problem

$$x_{kj} \leq y_k \quad \forall k \in K, j \in J \quad (47)$$

it will not change the problem structure. Now by removing constraint (43) on the number of winners, the problem turns into an instance of the CFCFLP problem with non-fractional demand. In our problem, a demand node is a bid package with unit demand, a candidate facility is a carrier $k \in K$, the transportation cost between a facility and demand node is the carrier's bid price for that package, and the facility cost corresponds to that carrier's penalty cost. Finally, the cost per unit distance per unit demand is 1. Since the CFCFLP problem is known to be NP-hard, by adding constraint (43) and non-fractional demand constraint, the BAP-P problem is also NP-hard.

Lemma 4.5: The bid analysis problem BAP-P with shipper's business constraints in unit procurement auctions is an NP-hard problem.

Inspired by the resemblance of the BAP-P problem to the facility location problem, we developed the following greedy and optimization-based heuristics to solve the bid analysis problem.

4.4.1 Greedy Algorithms

These algorithms either construct a solution from the ground up or try to improve from an initial solution. In addition we combine the two approaches in a hybrid heuristic. They are "greedy" in nature because in each step we choose the best carrier or bid package that can reduce total costs as much as possible.

Heuristic Construction Algorithms

We use two approaches to construct a base of winning carriers: sequentially adding more carriers into or dropping carriers from that base. We call the first one a Modified ADD algorithm (MADD) and the second one a Modified DROP algorithm (MDROP).

In the MADD algorithm, we gradually add more carriers into the winner set to see if we can further improve the solution. At the beginning, we assume each bid package is assigned to a dummy carrier with very large bid prices. Then at each iteration, we select a winner who can reduce the total cost at the greatest amount or increase the total cost at the least amount without violating other constraints. This procedure is continued until either, (1) the minimum-number-of-winners constraint is satisfied and adding more carriers will result in cost increment; or, (2) the maximum-number-of-winners constraint will be violated if more carriers are added. Letting TC = total cost including transportation costs and penalty costs.

Specifically, we select winners with iterative steps: let the set of winning carriers be K_n at iteration n . First we do not consider the $[T_{\min}^k, T_{\max}^k]$ bound and for each carrier $r \notin K_n$, we compute TC_r – the total cost if this carrier r is added into K_n . Then we temporarily add the carrier with the minimal TC_r to the winner set and assign this carrier with all packages which it has a less bid price.

In this procedure, some winners might violate the $[T_{\min}^k, T_{\max}^k]$ bound, so we need to balance traffic lanes among winners in next step. If a carrier k wins only a number of

packages less than T_{\min}^k , then we balance the traffic volume in the following way. For each package carrier k does not win, calculate the incremental of bid price if this bid package is assigned to k , assign these packages to this carrier according to the increasing order of this bid price increment under the condition that other carriers still have enough packages. This process is continued until constraint (6) is satisfied for each carrier. A similar balancing process can be implemented for those winners with the number of assigned packages greater than T_{\max}^k .

Note that after we balance traffic lanes among winners, the total cost could possibly exceed the cost of adding another carrier. If that occurs, repeat the process to check whether adding another carrier instead will result in a better balanced assignment. As a result, there might be a back-and-forth process between the third and fourth steps in the procedure.

The MDROP algorithm works in a similar manner. Initially for each bid package, we select the carrier with the minimum bid price to serve that package and add that carrier into our set of winners. If the total number of winning carriers exceeds K_{\min} , then we check which carrier to be dropped will result in the maximum savings. We greedily continue our search until either no further cost reductions can be found or the total number of winning carrier drops to K_{\min} . The lane balancing step is similar to that in the MADD algorithm.

In the MADD and MDROP algorithms, we add winners first and balance lanes second. It is also noticed that this process can be reversed, that is, we can balance lanes first and add winners second. The procedure is similar so we omit the details here.

Heuristic Improvement Algorithms

Given a feasible solution to the bid analysis problem using either construction algorithm, we can further improve on the solution through exchange of bid packages or substitution of carriers. In particular, a heuristic improvement algorithm can be implemented following these two steps:

1. Keep the winning carrier set, exchange bid packages among carriers within this set. This reduces to an assignment problem where bid packages are assigned to a fixed number of carriers with minimal total bid prices. Heuristics for assignment problems can be applied here with small modifications.
2. Keep the number of winning carriers and assignment of bid packages, but substitute one winner with another carrier not in the set of winners to see whether solutions can be further improved. This approach is easy to implement.

Finally, a combination of heuristic construction algorithm and improvement algorithm will result in a hybrid heuristic algorithm. In this paper, we are more interested in optimization based heuristic algorithms than greedy algorithms. Indeed, we found a Lagrangian relaxation based approach performs much better with reasonable computing time.

4.4.2 Lagrangian Relaxation Approach

In this section, we propose a Lagrangian relaxation based approach to solve the bid analysis problem BAP-P. Lagrangian relaxation is a very efficient optimization-based approach to solving a number of combinatorial optimization problems (Fisher, 1981).

The structure of the bid analysis problem suggests a number of relaxations on different constraints. Due to the strong similarity between this problem and the facility location problem, we only dualize constraint (42) in the BAP-P problem with unsigned Lagrangian multipliers $u = (u_1, \dots, u_j, \dots)$ and obtain the following Lagrangian relaxation problem:

BAP-P-LR

$$\max_u \min_{x,y} \sum_k \sum_j (c_{kj} + u_j) x_{kj} + \sum_k p_k y_k - \sum_j u_j$$

s.t.

$$K_{\min} \leq \sum_k y_k \leq K_{\max}, \quad (48)$$

$$T_{\min}^k y_k \leq \sum_j x_{kj} \leq T_{\max}^k y_k, \quad \forall k \in K \quad (49)$$

$$y_k, x_{kj} \in (0,1) \quad (50)$$

Next we discuss how we solve each instance of this relaxed problem BAP-P-LR to

optimality in polynomial time given a vector of Lagrangian multipliers.

First note that the relaxed Lagrangian problem BAP-P-LR can be modeled as a network flow problem. In the following graph, we need to push a flow with a total volume L from dummy node s to dummy node t via intermediate node k (carrier) and j (package) at the minimal costs. Each node k has a capacity bound $[T_{\min}^k, T_{\max}^k]$ and a penalty cost p_k , each edge linking k and j has an adjusted cost $\widetilde{c}_{kj} = c_{kj} + u_j$.

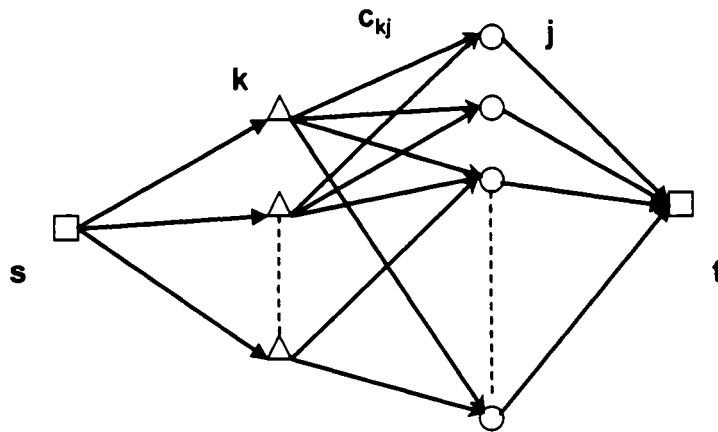


Figure 4.2 Network Flow Interpretation for the Lagrangian dual

Inspired by this observation, we developed the following solution approach. For each carrier, we first build a list of bid packages T_k . We associate each carrier k with a sorted list of \widetilde{c}_{kj} , then we continuously add a package j into T_k from an increasing order of \widetilde{c}_{kj} . This procedure stops when either (1) the size of T_k is equal to T_{\min}^k and the next \widetilde{c}_{kj} in the list is greater than zero; or (2) \widetilde{c}_{kj} is still less than zero but the size of $T_k = \sum_j x_{kj} = T_{\max}^k$.

Now for each carrier, we have a list of candidate packages T_k and the total cost $TC_k = p_k + \sum_j \{\widetilde{c}_{kj} \mid j \in T_k\}$. Next we sort all carriers in increasing order of TC_k . Then we add the K_{\min} number of carriers with smallest TC_k into the winner set K_{opt} ; for the rest of carriers, we continue to add those with $TC_k < 0$ into the winner set K_{opt} until the constraint $\sum_k y_k \leq K_{\max}$ is violated.

Finally, we let $y_k = 1$ for all $k \in K_{opt}$ and $y_k = 0$ for other carriers. Further, we set $x_{kj} = 1$ for all bid packages in the list T_k , that is, $k \in K_{opt}$ & $j \in T_k$, and $x_{kj} = 0$ for others.

Now this solution is an optimal one to the Lagrangian problem BAP-P-LR with u_j and is also a lower bound to the original bid analysis problem. In addition, this solution approach can be implemented in polynomial time. In each iteration, the time to solve a relaxed Lagrangian problem is $O(sK * Sort(sJ))$, where sK is the total number of carriers and $Sort(sJ)$ is the time to sort bid prices for sJ number of bid packages. There are many good sorting algorithms with polynomial running time.

Once we can find an optimal solution for the Lagrangian problem, we need to construct a feasible solution for the original BAP-P problem.

Note that an optimal solution for the Lagrangian problem may violate constraint 4 ($\sum_k x_{kj} = 1$) in the BAP-P problem with either of the following two variable sets:

1. A bid package is not covered, that is, $\sum_k x_{kj} = 0$ for some j ;

2. A bid package is covered by more than one carrier, that is, $\sum_k x_{kj} \geq 2$ for some j ;

For the first case, we simply assign such a bid package j to the best carrier k^* such that:

$k^* = k^* \mid c_{k^*j} \leq c_{kj}, \forall k \in K_{opt}$, where K_{opt} is the optimal winner set.

For the second case, we will risk making some carriers win less packages than their T_{min}^k if we simply remove redundant carriers for each bid package. As a result, the following heuristics is developed to tackle with this case.

(1) if $\sum_{k \in K_{opt}} T_{min}^k > sJ$, where sJ is the total number of bid packages;

This situation often occurs when shippers have to choose some large carriers but not all of them. However, the optimal solution might pick more carriers than shippers can afford. As a result, we need to either remove some carriers from the set of winners or substitute some carriers with others having less T_{min}^k . Let $f = \sum_{k \in OPT} T_{min}^k - sJ$, the

procedure can be implemented as:

- If $\sum_{k \in K_{opt}} y_k > K_{min}$, for each carrier k , compute the incremental cost of removing this carrier and assigning its packages to other carriers in K_{opt} . Remove the carrier who will result in the minimal increment of costs until $\sum_{k \in K_{opt}} T_{min}^k \leq sJ$ is

satisfied.

- If $\sum_{k \in K_{opt}} y_k = K_{min}$, for each carrier $k \in K_{opt}$, compute the incremental cost of by removing this carrier from the set of winners and assigning its lanes to other carriers not in K_{opt} . Substitute the carrier whose removal will result in the minimal increase in costs with its corresponding carriers not in K_{opt} until $\sum_{k \in K_{opt}} T_{min}^k \leq sJ$ is satisfied.

(2) if $\sum_{k \in K_{opt}} T_{min}^k \leq sJ$

In this situation, we only need to reassign packages among winning carriers such that each of bid packages is served by only one carrier.

- For each package $j \mid \sum_k x_{kj} \geq 2$, remove redundant carriers as follows:

$$\text{Set } x_{k^*j} = 1, \text{ if } k^* = \min_k \{c_{kj} \mid x_{kj} = 1\}; x_{kj} = 0 \quad \forall k \neq k^*$$

- Now each package j is connected to only one carrier, then we check whether each carrier's T_{min}^k constraint is satisfied. Split the set of winners K_{opt} into two subsets:

$$P = \{k \mid \sum_j x_{kj} < T_{min}^k\} \text{ and } Q = \{k \mid \sum_j x_{kj} \geq T_{min}^k\}$$

For each $k \in Q$, sort $c_{kj} | x_{kj} = 1$ into a list with increasing order, identify T_{\min}^k number of packages at the top of this list, put the rest of packages into a set RQ_k , note the size of $RQ_k = \sum_j x_{kj} - T_{\min}^k$. Let $RQ = \cup_{k \in Q} RQ_k$. This set includes all candidate packages that can be reassigned to carriers in P .

Now for each package $j \in RQ$, compute the incremental price if it is not served by its assigned carrier $k' \in Q$, instead, by a carrier $k \in P$, that is, $c_{kj} - c_{k'j}$. Start from the triplet (k, k', j) with the least incremental increase in price, let $x_{kj} = 1$ and $x_{k'j} = 0$, remove package j from set RQ . Once carrier k has enough demand such that $\sum_j x_{kj} = T_{\min}^k$, remove k from set P . Repeat this procedure until set P is empty.

Now this solution is indeed a feasible one to the original bid analysis problem BAP-P, and it also provides an upper bound to the problem. In addition, this heuristic algorithm of finding feasible solution can be implemented in $O(sJ * \text{sort}(sK))$ time.

We can further improve the Lagrangian lower bound and reduce the gap between the upper bound and lower bound. There are alternative ways to do this, among them is the well-known subgradient search method. Let $Z_0(u_i'')$ be the optimal solution from the Lagrangian problem BAP-P-LR (lower bound) and x'', y'' be the optimal assignment at iteration step n , and let Z^* be the feasible solution (upper bound), the subgradient search method starts with an initial value u^0 for the Lagrangian multipliers and updates them over the iterations as:

$$u_j^{n+1} = u_j^n + t_n (\sum_k x_{kj} - 1) \quad (51)$$

where:

$$t_n = \frac{\lambda_k (Z^* - Z_0(u_j^n))}{\sum_j (\sum_k x_{kj}^n - 1)^2} \quad (52)$$

In the above equation, t_n is a scalar satisfying $0 < t_n \leq 2$, normally we have $t_0 = 2$ and it will be halved whenever $Z_0(u_j^n)$ has failed to increase in a fixed number of iterations.

To summarize, the procedure for Lagrangian relaxation based approach is as the following:

1. Relax constraint (42), start from $u = u_0$, solve a relaxed Lagrangian problem BAP-P-LR to optimality;
2. Find a feasible solution for the original BAP-P problem from the optimal solution of BAP-P-LR using the heuristics we describe;
3. Check whether any stopping rule is satisfied, if not, go to the next step, else stop the program. Common stop rules include whether the lower bound is close to the upper bound and whether there have been too many iterations;
4. Update Lagrangian multipliers u using the Subgradient method and return to step 1.

4.4.3 Experimental Results

Numerical experiments were developed to examine the performance of our heuristics including MADD, MDROP and Lagrangian relaxation based method. In particular, we implemented these algorithms on a suite of randomly generated problems and compared their solution qualities and running time.

In order to implement our Lagrangian relaxation based method, we need to specify several system settings. First, as indicated above, the running time of the Lagrangian relaxation based method is closely related to the performance of the sorting algorithm. In our experiments, we used the quicksort algorithm (Cormen et al, 2001) with a running time $O(n \log n)$. As a result, the running time of our Lagrangian relaxation based method is $O(K * L * \log L)$.

The solution quality of Lagrangian relaxation based method also heavily depends on the choice of initial values for Lagrangian multipliers. We explored a few initial values and found the following two perform best on average:

$$u_j^0 = u^0 = \sum_{k,j} c_{kj} / sJ + \sum_k p_k \quad \text{and} \quad u_j^0 = \sum_k c_{kj} \quad (53)$$

As a result, we use these two to generate initial values for Lagrangian multipliers in parallel and stop the program whenever either of them finds a near optimal solution. In addition, the subgradient method is used to update Lagrangian multipliers during the program. The initial value of positive scalar λ_k is set to 2, and is halved whenever the

optimal solution for the relaxed problem cannot be improved in 4 successive iterations.

Further, the following rules are deployed to determine whether we should stop the iterations of Lagrangian relaxation based method:

1. Optimal solution is found (optimal solutions for Lagrangian problem are also feasible to the original problem, or the best upper bound is equal to the best lower bound);
2. Near optimal solution is found (upper bound – lower bound < 0.001);
3. The total number of iterations exceeds 2000 (we allow the program to run up to 4000 iterations if the solution is not good and the running time is small);
4. λ_k is too small ($\lambda_k < 1e-10$);

In this experiment, we use solution quality and running time to measure the performance of different algorithms. In terms of solution quality, we examine the gap between solutions from our heuristic algorithms and optimal solutions from commercial optimization software CPLEX version 8.1. For very large problems which CPLEX cannot solve to optimality within a working day, we evaluate the performance based on the gap between upper bound and lower bound in Lagrangian relaxation based method, and the gap between greedy algorithm solutions and Lagrangian upper bound.

Two data sets are developed for this purpose in our experiments. In practice a transportation procurement auction involves a dozen to several hundreds of carriers and a few hundreds to ten thousands of lanes (Caplice and Sheffi, 2003). Therefore we

designed our test data sets including a set of small problems (20 to 50 carriers and 200 to 400 lanes) and another set of large problems (100 to 500 carriers and 2000 to 10000 lanes). It is noted in our experiments that CPLEX can solve most problems in the first set within a working day, but it cannot guarantee to solve the large problems in the second data set even if given much longer computation time. (All experiments conducted on an AMD Athlon 1200 machine with 512 MB memory). The size of each problem set is listed in Table 4.3 and 4.4. For each type of problem, we tested a dozen instances and the results are presented as the average over those instances.

Input data for each problem includes each carrier's bid prices, penalty cost, minimum and maximum number of lanes if this carriers is a winner, minimum and maximum number of winners. In our experiments, a carrier's bid price c_{kj} is randomly distributed between 10 and 100, and the penalty cost is randomly distributed between 0 and 3% of total bid prices. Please note that this method of generating test data is without loss of generality because of the structure of the unit auction. If this were a general combinatorial auction then input data would have to come either from a real world dataset or from data generated over a transportation network. We set $K_{\min} = 5$ and K_{\max} is set to be the number of bidders. In addition, each carrier has a T_{\min}^k that is uniformly distributed over $[1, sJ/1.5K_{\max}]$ and $T_{\max}^k \in [sJ/1.5K_{\min}, sJ]$.

The numerical results are summarized reported from Table 4.3 to Table 4.6. Table 4.3 lists both optimal solution by CPLEX and near-optimal solution obtained using the heuristic algorithms for small problems. The gap between the lower bound and upper

bound solution given by the Lagrangian based method is very tight and the ratio between them is above 97% almost in all cases; in addition, the Lagrangian feasible solution is also very close to the optimal solution. Surprisingly, even though greedy algorithms do not perform as well as the Lagrangian based method, their solutions are close to optimal as well. Further, the solution by MDROP algorithm is slightly better than the MADD solution, but the difference might not be statistically significant.

As shown in Table 4.4, the computation time used by CPLEX is not comparable with the heuristic algorithms. The CPLEX solution time increases exponentially with the size of problems and in some cases this time exceeds 10 hours for a relatively small problem while the heuristic algorithms can solve these in less than 1 minute. As was expected, the time used by the Lagrangian based method is slightly higher than those of the greedy algorithms.

Table 4.3 Average Solution Quality of Small Bid Analysis Problems

Case Index	1	2	3	4	5	6	7	8	9
Carrier size	20	20	20	30	30	40	40	40	50
Lane size	200	300	400	300	400	300	400	500	400
Lower/ Upper	.998	.999	.993	.996	.969	.974	.979	.975	.979
Upper/ CPLEX	1.0	1.0	1.0	1.0	1.0	1.001	1.001	1.0	1.0
MADD/ CPLEX	1.01	1.0	1.001	1.007	1.003	1.009	1.004	1.002	1.003
MDROP/ CPLEX	1.0	1.0	1.001	1.0	1.0	1.003	1.001	1.001	1.001

Table 4.4 Average Computation Time for Small Bid Analysis Problems (Minutes)

Case Index	1	2	3	4	5	6	7	8	9
CPLEX time	0.5	2.2	9.2	10.8	66.3	66.2	137	231	192
Lagrangian time	0.6	0.3	0.6	0.5	0.7	0.6	0.8	0.7	0.7
MADD time	0.03	0.03	0.03	0.04	0.04	0.05	0.06	0.06	0.07
MDROP time	0.00	0.01	0.01	0.02	0.03	0.03	0.04	0.04	0.05

The performance of the Lagrangian based method is constant with the increase of problem size as indicated in Table 4.5 and 4.6. Even with a very large problem size of 500 carriers and 10,000 lanes, the gap between lower bound and upper bound is less than 1%. And its computation time is less than 4 hours.

However, the performance of the greedy algorithms deteriorates when the problem size is relatively large. Even though the average ratio between their solutions and feasible solutions given by Lagrangian based method (upper bound) is less than 1.1 on average, we have spotted cases where this ratio exceeds 1.3. The advantages of these greedy algorithms are clearly fast computational times.

Table 4.5 Average Solution Quality of Large Bid Analysis Problems Under Alternative Heuristics

Case Index	11	12	13	14	15	16	17	18	19
Carrier size	100	100	200	200	300	300	400	400	500
Lane size	2000	4000	4000	6000	6000	8000	8000	10000	10000
Lower/ Upper	.992	.969	.979	.990	.996	.993	.990	.991	.990
MADD/ Upper	1.057	1.051	1.063	1.063	1.070	1.067	1.068	1.090	1.080
MDROP/ Upper	1.056	1.050	1.058	1.062	1.065	1.066	1.067	1.076	1.071

Table 4.6 Average Computation Time for Large Bid Analysis Problems (Minutes)

Case Index	11	12	13	14	15	16	17	18	19
Lagrangian time	6	14	31	48	76	101	136	181	225
MADD time	0.4	0.4	0.6	1	1.1	1.4	2.1	4	7.6
MDROP time	0.5	1.1	3.9	6.6	13.9	20	34	46	69

In summary, both greedy algorithms and Lagrangian based heuristics have an unbeatable advantage over exact algorithms. The latter cannot be guaranteed to solve practical bid analysis problems. Further, the Lagrangian based algorithm can provide feasible solutions that are very close to optimal.

CHAPTER 5

COMBINATORIAL AUCTIONS

This chapter considers the bid analysis problems faced by shippers involved in combinatorial auctions for the procurement of transportation services with additional shipper's non-price business constraints. For many years, large shippers have deployed a variety of B2B auctions to procure transportation services from common carriers based on periodically renewed contracts. Combinatorial auctions have become famous for their efficient handling of carrier's economies of scope. However, the bid analysis problem in combinatorial auctions is a complex problem and the shipper's non-price business constraints further complicate this matter. This chapter examines this problem by formulating the shipper's business constraints, namely min-max carriers, coverage and favoring of incumbents, as side constraints in integer-programming models. Two different formulations are presented to tackle this problem based on the differentiation between "contracts" and "loads". The assumption is that a contract is a unit and modeled as binary variable as a single sourcing decision. The "loads" help in the multiple sourcing decision making and are modeled as continuous variables. Lagrangian relaxation based algorithms are developed to solve the bid analysis problems. The experimental performance of this approach is further analyzed with empirical benchmarking on a set of randomly generated problems.

5.1 INTRODUCTION

Business-to-business (B2B) procurement auctions have become a dominant price discovery mechanism to assist shippers to develop strategic contractual relationships with transportation service providers (carriers). In recent years, shippers have found it

beneficial to use combinatorial reverse auctions for transportation service contract procurement and to allow carriers bid for packages of lanes instead of individual lanes (Sheffi, 2004).

In a combinatorial auction, shippers do not pre-define packages of lanes to bid and carriers have flexibility to combine multiple lanes into their preferred packages and to bid for conditional bids. As a result, there might be overlapping between different carriers' packages, as well as within a single carrier's own packages. Furthermore, carriers' valuations on different packages are often not additive. That is, the sum of the prices for two separate bid packages may not be equal to the price for a package that includes the union of the two packages. The sheer number of possible combinations creates a very difficult problem for shippers who must determine winners and assign lanes so as to minimize procurement costs. As a matter of fact, this bid analysis problem, also called the winner determination problem (WDP) in general combinatorial auctions, is NP-complete in most cases (de Vries and Vohra, 2003). The shippers also have to decide on the form of auction, whether to i) single source or split the lanes; ii) single round or multiple round bidding; and iii) have a closed or open auction.

Further, shippers often have to consider certain non-price business requirements when they analyze the bids (Caplice and Sheffi, 2003). For instance, a shipper often has an idea of approximately how many carriers they would like to have as partners and as well as the maximum loads to be allocated to each winning carrier. These side constraints further complicate the bid analysis problem. In an earlier paper Song, Regan and Nandiraju (2005), they examine a simpler problem in which the shipper identifies

mutually exclusive and collectively exhaustive bundles of lanes a priori. In practice many companies prefer these so called unit auctions because of their relative simplicity for bidders and auctioneers and because they allow shippers more control over the structure of the contracts awarded.

In this chapter, we first review the bid analysis problem in transportation procurement auctions, particularly in combinatorial auctions. We then discuss how to incorporate the shipper's business constraints into the bid analysis problem and present integer-programming models for this problem. Further, we propose Lagrangian relaxation based solution algorithms. Numerical results are presented to analyze the behavior of our algorithm. Finally, we offer conclusions and discuss future research directions.

5.2 LITERATURE REVIEW

Combinatorial reverse auctions are those in which multiple heterogeneous items are put out to bid simultaneously by buyer (auctioneer) and in which sellers (bidders) can bid on combinations of these items (de Vries and Vohra, 2003). These are considered especially useful when the bidder has non-additive preferences among the goods being auctioned. In the transportation procurement scenario, the items put out to bid are lanes, with shipper specified demands. In this paper we look into a single round closed combinatorial auction. The bidding language used is an OR. Sourcing decisions usually involve multiple criteria in selecting the carriers. Multi-attribute auctions relate to items that can be differentiated on several non-price attributes such as quality, delivery date etc. Transportation auctions are multi-attribute auctions in the context that bidding items (a 'lane') have other non-price attributes like service quality and delivery time windows.

Typically these attributes are factored into the bid prices while pre-screening and the bid prices are updated by assigning weights to each of these attributes. It is also interesting to consider both *single sourcing*, in which the shipper chooses a single carrier, and *multiple sourcing* (split lanes), in which there are multiple lanes to procure and the shipper is willing to consider a solution that aggregates each lane across multiple carriers.

Caplice (1996) was the first to examine the use of combinatorial auction mechanisms for bidding in a long-term contract truckload market. Ledyard, Olson, Porter, Swanson and Torma (2002) present a “combined value” model based multi-round combinatorial reverse auction conducted in 1994 for the procurement of contracts of serving over eight hundred lanes (delivery routes) for Sears Logistics Services. Elmaghraby and Keskinocak (2003) report the use of multi-round combinatorial auction for long term contracting at Home Depot. Logistics.com, Accesstransporta.com (Canada), Translogistica.com (UK) have reported the use of combinatorial auction methods for long term contracting. Song and Regan (2003) and Song and Regan (2004) developed optimization based bidding strategies for carriers bidding in these auctions.

In this chapter we develop heuristics to solve the winner determination problems with a side constraint on the number of winning carriers in both single sourcing and multiple sourcing auction mechanisms. The two primary components of computational complexity faced by the auctioneer (a shipper) in an auction mechanism are the allocation rule and the payment rule. In order to allocate winning bids an optimization problem needs to be solved typically referred to as the winner determination problem (WDP). The complexity

of the WDP depends on auction setting, the number of items sold and the number of bidders.

The winner determination problem for forward combinatorial auctions has a standard set packing formulation, which is NP hard. de Vries and Vohra (2003) provide a comprehensive survey of combinatorial forward auctions. Exact methods to solve the WDP in these auctions have been proposed by Fujishima, Brown and Shoham (1999) as well as Sandholm (1999) using dynamic programming and tree-based branch and bound methods respectively. Andersson, Tenhunen and Ygge (2000) use an integer programming approach to solve the WDP. Combinatorial reverse auctions have a set covering formulation, which is NP hard (Sandholm and Suri, 2001). Set packing, covering formulations under special cases allows for polynomial time solutions. All these special cases arise out of constraints that reduce the constraint matrix to be totally unimodular.

As discussed in Caplice and Sheffi (2003), shippers have a variety of business constraints when they assign bids to carriers as explained in Chapter 2. Sheffi (2004) notes that the shippers do not generally require an optimal solution in combinatorial auctions, and also mention that including the side constraints into the optimization problem is of utmost necessity. Some shipper's conduct screening in the bid preparation stage to ensure that bidders can satisfy their service level requirements and identify the core carriers. Another way to model this constraint is to modify the cost coefficients of individual carriers by either a multiplicative or an additive factor.

The complete incorporation of all these constraints requires building a

sophisticated decision support system and is beyond the scope of our study. In this work, we only consider the business constraints, which apply across the system, not on individual lanes or at the facility level. We assume that the service backup issue and performance factors are already addressed in bid preparation stage or incorporated into the coefficient cost.

Sandholm and Suri (2001) present the side constraints and other non-price attributes in combinatorial auctions in real world electronic markets and discusses computational complexities of the market clearing mechanisms. As mentioned earlier, Song, Regan and Nandiraju (2005) also develop carrier assignment formulations in unit procurement auctions (shippers determines packages) incorporating the above side constraints in the auctions in which the items are to assigned are packages of lanes.

5.3 COMBINATORIAL AUCTION ALGORITHMS

Notation:

i : index of a lane in set L ;

j : index of a bid package in set J which may include multiple lanes

k : index of a bidding carrier in set K ;

c_{kj} : shipper's cost to select carrier k to serve package j ;

f_{kj} : shipper's cost per unit volume to select carrier k to serve package j ;

p_k : penalty cost for carrier k to be selected as a winner, $p_k \geq 0$;

K_{\max} : maximum number of carriers to be selected as winners;

K_{\min} : minimum number of carriers to be selected as winners;

V_{kj} : volume bid by carrier k for package j ;

V_{kj} : estimated volume package j ;

V_i - estimated volumes on lane i

V_{ki}^i - volume bid by carrier k on lane i in bid j

c_{ki}^i - bid price per unit for lane i in bid j by carrier k .

We also have the following decision variables:

x_{kj} : binary variable indicating whether a carrier k wins package j ;

y_k : binary variable indicating whether a carrier wins anything at all.

5.2.1 Single Sourcing

The model presented below is a single sourcing model, which means is that volumes on a lane or a set of lanes will be awarded to the carrier. The carrier who wins the lanes wins all the volume traffic in that particular lane and all the lanes that a bidder wins in that bid.

$$\min \sum_k \sum_j c_{kj} x_{kj}$$

s.t.

$$\sum_k \sum_j a_{kj}^i x_{kj} = 1, \quad \forall i \quad (1)$$

$$x_{kj} \in (0,1) \quad (2)$$

Constraint (1) specifies that each lane must be included in at least one package. The formulation above represents the reverse combinatorial auction formulation, which

takes the form of a set-partitioning model (Balas and Padberg, 1976). Chv'atal (1979) presents a greedy heuristic for the set covering problem which can be used to obtain a myopic solution to the set-partitioning problem. For exact methods using branch and bound techniques the reader is referred to Garfinkel and Nemhauser (1969). Hoffman and Padberg(1993) develop a linear programming heuristic and apply it in a branch and cut framework for solving large scale set-partitioning problems encountered in air crew scheduling problems. Fisher and Kedia (1990) present a lagrangian relaxation approach in a branch and bound scheme to solve set covering/partitioning problems. The authors use dual heuristics to improve the solution of the lagrangian dual. Krueken, Fleurian and Peeters (2004) show that for set-partitioning problems a lagrangian relaxation based lower bound in branch and bound scheme solves in less time than a linear programming based lower bound.

5.2.2 Multiple Sourcing

In this model the carriers submit a bid with packages and the amount of truckloads they will serve for each package. The carrier who wins the lanes wins a part of volume traffic in that particular lane assigned by the shipper.

$$\begin{aligned}
 & \min \sum_k \sum_j \sum_i c_{kj}^i V_{kj}^i \\
 & s.t \\
 & \sum_k \sum_j V_{kj}^i x_{kj} = V_i, \quad \forall i \tag{3}
 \end{aligned}$$

$$x_{kj} \in (0,1) \tag{4}$$

The constraint (3) models that the loads for each lane in a package must be equal to the shippers demand for that lane. In computer science literature, a similar version of the problem with “greater than equal to” sign for constraint (3) is termed as the multi-unit combinatorial auction problem. The reader is referred to the following papers for the research into this problem, Brown, Tenenholtz, Shoham (2000), Gonen and Lehmann (2000) and Sandholm and Suri, (2000).

5.3 WINNER DETERMINATION PROBLEM WITH INCUMBENCY CONSTRAINTS

In this section we develop the formulation and lagrangian heuristic for the winner determination problem for combinatorial auction with the inclusion of incumbency side constraints. Following the notation defined above the bid analysis problem for a single sourcing case is as follows:

WDP-IC:

$$\min \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k$$

s.t.

$$\sum_k \sum_j a_{kj}^i x_{kj} \geq 1, \quad \forall i \tag{5}$$

$$\sum_j x_{kj} \geq y_k, \quad \forall k \tag{6}$$

$$x_{kj} \leq y_k, \quad \forall k, \forall j \quad (7)$$

$$y_k, x_{kj} \in (0,1) \quad (8)$$

The objective function of WDP-IC formulation minimizes total procurement costs including the actual “bid” price and the incumbent penalty cost. We model the problem in slightly different form using set covering constraints instead of the set-partitioning constraints. Constraint (5) ensures each lane can be assigned to more than one package, giving rise to primary and alternate carriers for a lane and models the case of “free disposal”. In a free disposal the shipper can contract the lane to another secondary carrier but may not provide any business to that carrier. Constraint (6) and (7) are the coupling constraints between x_{kj} and y_k . Constraint (6) ensures that if a carrier is selected at least one package bid from the carrier is allocated. Constraint (7) packages from a carrier can be allocated only if the carrier is selected for the final award.

Lemma 5.1: WDP-IC is NP-hard.

The WDP-IC formulation reduces to a classical weighted set partitioning problem, which is well known to be NP-hard (Balas and Padberg, 1976) without the inclusion of penalty cost included in the objective function.

5.3.1 Solution Algorithm

We apply a lagrangian relaxation method to solve the problem by relaxing the set covering constraints (5).

WDP-IC-LR

$$\min \sum_k \sum_j (c_{kj} - \sum_i a_{kj}^i \mu_i) x_{kj} + \sum_k p_k y_k + \sum_i \mu_i$$

s.t.

$$\sum_j x_{kj} \geq y_k, \quad \forall k \quad (9)$$

$$x_{kj} \leq y_k, \quad \forall k, \forall j \quad (10)$$

$$y_k, x_{kj} \in (0,1) \quad (11)$$

The following lagrangian dual has the property of being integrality property, which means that the lagrangian dual is not going to better than the linear relaxation of the original problem. (Here show the results of the experiments showing weak LP relaxation results).

Optimal solution for a relaxed Lagrangian problem

The optimum solution for the relaxed lagrangian problem is as follows:

- Select the packages for which $(c_{kj} - \sum_i a_{kj}^i \mu_i) < 0$ and tentatively make a list *LIST* of all these packages.
- Now based on this list we have to set the packages for y_k . Sort the list *LIST* by various carriers to generate K_j^1 . Set $y_k = 1$, iff $p_k + \sum_{k \in K^1} c_{kj}^1 < 0$, from this list set all $x_{kj} = 1$ all else to 0.

Feasible heuristic generation

This procedure is called iteratively after solving the lagrangian dual. This procedure tries

to find the lagrangian feasible solution using the lagrangian dual solution. The following are the steps for the feasible solution generation:

Feasible solution heuristic (\tilde{c}_{kj}, μ)

- Sort the lanes in the descending values of μ_i .
- Do until $L = \phi$
 - Pick the lane $i \in L$ with the highest μ_i .
 - Then pick the package with lane i with the lowest \tilde{c}_{kj} and assign the this lane to the package.
- Calculate the Upper bound.

5.3.2 Greedy Heuristic

In this section we develop a primal heuristic to get a greedy solution to the WDP-IC formulation. The greedy heuristic provides an upper bound to the problem.

B : greedy bid set

G : set of carriers allocated

L : set of all lanes

- Initialize: $G = \phi, B = \phi, L = I$
- Sort the packages by $\{c_{kj} / |B_{kj}| + p_k \delta_k\}$ where $\delta_k = 1$ if $k \in G$ else 0.
- Find the minimum package b_{kj}^{\min} and add the package bid set $B = B \cup b_{kj}^{\min}$. Set

$G = G \cup k$ Remove all the lanes from $\forall l, l \in b_{kj}^{\min}$ from set L .

□ Do until $L = \phi$

The following algorithm works but sometimes gives sub optimal solutions. In the step where we update and sort packages, the sort cost function must somehow include the already used lanes in the solution at every iteration. The cost of adding a package depends on the lanes already covered in the solution. The computational complexity of the heuristic is $O(|I||B|\log(|B|))$.

5.3.3 Subgradient Optimization

Let $Z_n(\mu^n)$ be the optimal solution from the Lagrangian problem WDP-LR (lower bound) and x^n, y^n be the optimal assignment at iteration step n , and let Z_n^* be the feasible solution (upper bound), the subgradient search method starts with an initial value μ^0 for the Lagrangian multipliers and updates iteratively in the following way:

$$\mu_i^{n+1} = \max \{ \mu_i^n + t_n (1 - \sum_k \sum_j a_{kj}^i x_{kj}^n), 0 \} \quad (12)$$

where:

$$t_n = \frac{\lambda_n (Z_n^* - Z_n(\mu^n))}{\sum_i (1 - \sum_k \sum_j a_{kj}^i x_{kj}^n)^2} \quad (13)$$

In the above equation, λ_n is a scalar satisfying $0 < \lambda_n \leq 2$, normally we have $\lambda_0 = 2$ and it will be halved whenever $Z_n(\mu^n)$ has failed to increase in a fixed number of iterations. The iterative search for optimal solutions will stop when certain rules are

satisfied. These rules normally include: optimal or near-optimal solution is found; there are too many iterations; the scalar λ_n is too small.

5.3.4 Dual Heuristics

Dual problem is:

$$\max \sum_i \mu_i - \sum_k s_k$$

s.t.

$$\sum_i a_{kj}^i \mu_i + t_k - w_{kj} \leq c_{kj} \quad (14)$$

$$\sum_j w_{kj} - t_k - s_k \leq p_k \quad (15)$$

$$w_{kj} \geq 0, \quad t_k \geq 0, s_k \geq 0, \mu_i \geq 0 \quad (16)$$

where:

μ_i, s_k, w_{kj}, t_k are lagrangian multipliers for constraints (5), (6), (7), (8) respectively.

Finding the dual solution as well forming a condensed dual is not that easy. A condensed dual is generated from the dual problem by reformulation the dual problem as a function one dual decision variable and was used to solve the uncapacitated fixed charge location problem (Erlenkotter, 1978). Trying too form the condensed dual is also hard for WDP-IC as the dual problem has too many dual variables.

Fisher, Kedia (1990) used 3-opt heuristics to improve the lagrangian lower bound, but in our problem improving a particular dual variable might generate infeasible solutions for the overall dual problem. Hence we resort to aggregate fixing to obtain information from

the lagrangian solution about the value of a particular primal decision variable in the final solution.

Aggregate Fixing Reduction in problem size (aggregate fixing):

- Fixing decision variables y_k to zero. Solve the lagrangian dual if $y_k = 0$ and $Z_{l,B} + p_k > Z_{u,B}$, and hence y_k cannot be in the optimal solution.
- Fixing some decision variables to y_k to one. Solve the lagrangian dual if $y_k = 1$ and $Z_{l,B} - p_k > Z_{u,B}$, hence y_k cannot be in the optimal solution.

Using aggregate fixing we can reduce the problem size and present it to a branch and bound solver. In the empirical results page we will present the reductions we get using aggregate fixing on our test instances.

5.3.5 Input Data Generation

The test bid generation developed is similar to the methodology by Leyton-Brown, Pearson and Shoham (2004) but simplified somewhat. The following outlines the procedure used for input data generation. The following data generation method will be used for all the problems in the rest of the chapter unless specified.

Input:

1. A Euclidean network on an unit square: $G(V, A)$
2. The number of bids to be generated: num_bids
3. A cost factor for each lane: $d_{(n_1, n_2)}$

Procedure:

While($num_generated_bids \leq num_bids$)

1. Randomly choose two nodes, n_1 and n_2
2. Find the shortest path between the two nodes: $SP(n_1, n_2)$
3. Make an AND bid of lanes l in this path: $\forall l \in SP(n_1, n_2)$
4. Bid Price: $(1+r) * Cost(SP(n_1, n_2))$
5. Increment: $num_generated_bids = num_generated_bids + 1$

Other input data for each problem includes each carrier's bids, bid prices, penalty cost, minimum and maximum number of lanes if this carrier is a winner, minimum and maximum number of winners. In our experiments, a carrier's bid price c_{ki} has a random profit component r and a deterministic component based on distance. The penalty cost is randomly distributed between 0 and 10 with the incumbent penalties equal to 0. Note that this method of generating test problems is for preliminary tests of our solution method only. We set K_{min}, K_{max} to be randomly generated from the intervals $(1, 0.33 * |K|)$ and $(0.75 * |K|, |K|)$ respectively.

The lower bound in numerical results is the best lower bound obtained by solving the lagrangian dual of winner determination problems. The upper bound is found using the greedy algorithm presented above. The tables also list the optimal solution and time by commercial software CPLEX. All experiments conducted on an AMD Athlon 1200 machine with 512 MB memory. For each type of problem, we tested a dozen instances and the results are presented as the average over those instances.

5.3.6 Empirical Results

In table 5.1 we present the empirical results for small test cases. Lower/ CPLEX is the ratio of the lower bound to the optimal solution generated from CPLEX. Lower/Upeer is the ratio of the lower bound to the upper bound generated by the lagrangian heuristic. All the times (CPLEX, time, Lagrangian time) are in minutes.

Table 5.1 Average Solution Quality of Lagrangian heuristic for WDP-IC

Case Index	1	2	3	4	5
Carrier size	5	10	10	10	15
Lane size	10	15	15	20	25
Package size	30	40	50	60	75
Lower / Upper	0.99	0.99	0.99	0.99	0.98
Upper / CPLEX	1.00	1.00	1.01	1.00	1.00
CPLEX time	0.02	0.01	0.04	0.02	0.05
Lagrangian time	0.12	0.24	0.52	0.94	2.00

From the table we can see that the duality gap for WDP-IC is within 1% for small instances of the problem. WDP-IC takes the form of a set-covering problem and hence the results of the duality gap are very small, though computational times with respect to CPLEX are high. In the next section, we model the winner determination problems as set-

partitioning problems, which is a better representation of the transportation procurement.

5.4 WINNER DETERMINATION WITH MINIMUM MAXIMUM CARRIERS

In this paper we consider those shipper's business constraints as discussed in Caplice and Sheffi (2003): maximum and minimum numbers of winning carriers, and incumbent preference. The service backup issue, complete regional coverage and performance factors can be addressed at the bid preparation stage

Now, the bid analysis problem in combinatorial transportation procurement auctions is modelled as:

WDP-MMC:

$$\min \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k$$

s.t.

$$\sum_k \sum_j a_{kj}^i x_{kj} = 1, \quad \forall i \tag{17}$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \tag{18}$$

$$\sum_j x_{kj} \geq y_k, \quad \forall k \tag{19}$$

$$x_{kj} \leq y_k, \quad \forall k, \forall j \tag{20}$$

$$y_k, x_{kj} \in (0,1) \tag{21}$$

WDP-MMC formulation models the bid analysis problem faced by the shippers in single sourcing auction mechanisms. The objective function of this formulation minimizes total procurement costs including the actual "bid" price and the

penalty cost. The first constraint (17) ensures each lane can only be assigned to one package modeling the single sourcing constraint. Constraint (18) limits the number of winners that shippers want to have in their core carrier base. Constraint (19) and (20) are the coupling constraints between x_{kj} and y_k .

VWDP-MMC:

$$\min \sum_k \sum_j f_{kj} V_{kj} + \sum_k p_k y_k$$

s.t.

$$\sum_k \sum_j a_{kj}^i V_{kj} = 1, \quad \forall i \quad (22)$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (23)$$

$$\sum_j V_{kj} \geq y_k, \quad \forall k \quad (24)$$

$$V_{kj} \leq y_k, \quad \forall k, \forall j \quad (25)$$

$$y_k \in (0,1) \quad (26)$$

$$0 \leq V_{kj} \leq 1 \quad (27)$$

VWDP-MMC formulation models the bid analysis problem faced by the shippers in multiple sourcing auction mechanisms. The objective function of VWDP-MMC minimizes total procurement costs including the actual “bid” price per unit volume and the penalty cost. Constraint (22) ensures that the total volume on each lane is satisfied.

Constraint (24) and (25) are similar to constraints (19) and (20) respectively.

In this model we have $K_{\max} > K_{\min} \geq 1$. Further, note that the bid packages are not defined by shippers; instead, these are constructed and submitted by individual carriers. As a result, different packages may include common lanes. Also note that for the WDP-MMC without constraints (19) and (20) and the penalty cost included in the objective function, the problem reduces to a classical weighted set partitioning problem, which is well known to be NP-hard (Balas and Padberg, 1976). Suppose the incumbency constraint is removed, then the problem reduces to a combinatorial reverse auction problem with a constraint on the number of winners which is NP-hard for binary and continuous values of winning allocations (Sandholm, Suri, 2001). Hence both the WDP-MMC and the VWDP-MMC are NP-hard.

5.4.1 Lagrangian Relaxation for WDP-MMC

Relax constraint (17)

The problem structure makes it natural to consider relaxing constraint (17) in the WDP - MMC formulation as constraint (17) increases the complexity of the problem. Letting

$\mu_i \in R$ be the Lagrangian multipliers, we have:

WDP-LR

$$\begin{aligned} \min_{x,y} \quad & \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k + \sum_i \mu_i \{ \sum_k \sum_j a_{kj}^i x_{kj} - 1 \} \\ & = \sum_k \sum_j c_{kj}^1 x_{kj} + \sum_k p_k y_k - \sum_i \mu_i \end{aligned}$$

s.t.

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (28)$$

$$\sum_j x_{kj} \geq y_k, \quad \forall k \quad (29)$$

$$x_{kj} \leq y_k, \quad \forall k, \forall j \quad (30)$$

$$y_k, x_{kj} \in (0,1) \quad (31)$$

where: $c_{kj}^1 = c_{kj} + \sum_i \mu_i a_{kj}^i$, note c_{kj}^1 can be any real number.

The problem WDP-LR decomposes into a set of problems – one for every carrier used. Replacing the integrality constraints with a linear relaxation does not change the solution of WDP-LR. Hence, the lagrangian relaxation (LR) scheme is not ideal because it yields a maximum bound similar to the LP bound. However finding an LP bound can be cumbersome and constraint set (17) presents some formidable solution hurdles.

Finding an optimal solution for a relaxed Lagrangian problem

To solve this relaxed problem, suppose for each carrier we can find a list of packages J_k^* such that $\sum_j c_{kj}^1 x_{kj}$ can be minimized, then we compute $p_k + \sum_j \{c_{kj}^1 \mid j \in J_k^*\}$ for each k and then add these to a list. Then we select K_{\min} number of carriers from the decreasing order of the list. If there are still carriers remaining on that list such that

$p_k + \sum_j \{c_{kj}^l \mid j \in J_k^*\} < 0$, then we continue adding those carriers as long as the constraint

$\sum_k y_k \leq K_{\max}$ is satisfied.

To find packages in J_k^* , if $c_{kj}^l \leq 0$, we add package j into J_k^* for each carrier. For x_{kj} , we set $x_{kj} = 1$ only for those lanes that are already picked by carriers in the last step, that is $x_{kj} = 1, \forall j \in J_k^*$. The lagrangian dual provides a lower bound to the problem and the computational complexity for finding feasible lagrangian solution is $O(\text{sort}(|K|))$.

Cases to be considered while finding J_k^* :

- $\{c_{kj}^l \leq 0 \forall j \in J_k\}$ Add all $\forall j \in J_k$ into J_k^* ;
- $\{c_{kj}^l \leq 0 \forall j < j_1, c_{kj}^l > 0 \forall j \geq j_1\}$ Add all $\forall j < j_1$ into J_k^* ;
- $\{c_{kj}^l > 0 \forall j \in J_k\}$. We need to analyze the case where $c_{kj}^l > 0$, then we sort the vector and add only the $j^* = \min(c_{kj}^l)$. Add all j^* into J_k^* ;

The final solution is the optimum value for the lagrangian relaxation. The solution obtained from this method is equal to the linear programming relaxation, but finds the solution in polynomial time.

Finding a feasible solution for WDP(Primal heuristic)

To obtain the feasible solution using the lagrangian dual optimal solution carrier set K_{OPT} , we solve a set partitioning problem using the formulation:

WDP-SP

$$\min_{x,y} \sum_k \sum_j c_{kj}^1 x_{kj}$$

s.t.

$$\sum_{k \in k_{OPT}} \sum_j a_{kj}^i x_{kj} \geq 1, \quad \forall i \quad (32)$$

$$x_{kj} \in (0,1) \quad \forall k \in k_{OPT} \quad (33)$$

Set partitioning problem is NP-Hard (Balas and Padberg, 1976). The set covering and packing formulations naturally lends themselves to greedy starts (i.e. an approach that at every iteration myopically chooses the next best step without regard for its implications on future moves), see e.g. Fisher and Wolsey (1982). Interchange approaches have also been applied—here; a swap of one or more columns is taken whenever such a swap improves the objective function value.

Using the modified version of Chv'atal's (1979) set covering heuristic and applying the Chu-Beasley heuristic feasibility operator (1996), a feasible initial solution for WDP problem is found if it exists. This feasible solution is assigned as the initial upper bound.

We present an outline of a simple greedy algorithm used to find the upper bound during the course of lagrangian relaxation. The algorithm works as a primal heuristic in a Lagrangian relaxation as at every iteration c_{kj}^1 and Lagrangian multipliers μ are the input for this procedure to generate a feasible solution.

Feasible solution heuristic($c_{kj}^1, \mu, \tilde{x}_{kj}, \tilde{y}_k$)

- Sort the lanes in the descending values of μ_i .

- Do until $L = \phi$
 - Pick the lane $i \in L$ with the highest μ_i .
 - Then pick the package-containing lane i with the lowest c_{kj}^1 .
 - Remove all the lanes from this package $j \in J$ from L . $L = L / (\forall i \in j)$
- Calculate the upper bound.

During the iterative process the primal heuristic may not generate a feasible solution at a particular and we set the feasible solution to a large number at that iteration. In the next section we describe the Lagrangian relaxation for VWDP.

5.4.2 Lagrangian Relaxation for VWDP

Relax constraint (22)

$$\begin{aligned} \min_{x,y} \quad & \sum_k \sum_j f_{kj} x_{kj} + \sum_k p_k y_k + \sum_i \mu_i \{ \sum_k \sum_j a_{kj}^i x_{kj} - 1 \} \\ & = \sum_k \sum_j c_{kj}^2 x_{kj} + \sum_k p_k y_k - \sum_i \mu_i \end{aligned}$$

s.t.

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (34)$$

$$V_{kj} \leq y_k, \quad \forall k, \forall j \quad (35)$$

$$y_k \in (0,1) \quad (36)$$

$$0 \leq V_{kj} \leq 1 \quad (37)$$

where: $c_{kj}^2 = c_{kj} + \sum_i \mu_i a_{kj}^i$, note c_{kj}^2 can be any real number.

It is quite counterintuitive that solving the lagrangian dual for WDP and VWDP is similar but in fact we find that this is the case. To obtain the feasible solution using the lagrangian dual optimal solution carrier set K_{OPT} , we solve a fractional set-covering problem using the formulation:

$$\min_{x,y} \sum_k \sum_j c_{kj}^2 V_{kj}$$

s.t.

$$\sum_{k \in k_{OPT}} \sum_j a_{kj}^i V_{kj} \geq 1, \quad \forall i \quad (38)$$

$$V_{kj} \geq 0 \quad \forall k \in k_{OPT} \quad (39)$$

5.4.3 Subgradient Optimization

The feasible solution obtained with this procedure provides an upper bound for the original bid analysis problem, and we can further improve the lower bound solution by iterating the above Lagrangian procedures while updating the Lagrangian multipliers. There are alternative ways to do this, among them is the well-known subgradient search method. Let $Z_n(\mu^n)$ be the optimal solution from the Lagrangian problem WDP-LR (lower bound) and x^n, y^n be the optimal assignment at iteration step n , and let Z_n^* be the feasible solution (upper bound), the subgradient search method starts with an initial value

μ^0 for the Lagrangian multipliers and updates iteratively in the following way:

$$\mu_i^{n+1} = \mu_i^n + t_n \left(\sum_k \sum_j a_{kj}^i x_{kj}^n - 1 \right) \quad (40)$$

where:

$$t_n = \frac{\lambda_n (Z_n^* - Z_n(\mu^n))}{\sum_i \left(\sum_k \sum_j a_{kj}^i x_{kj}^n - 1 \right)^2} \quad (41)$$

In the above equation, λ_n is a scalar satisfying $0 < \lambda_n \leq 2$, normally we have $\lambda_0 = 2$ and it will be halved whenever $Z_n(\mu^n)$ has failed to increase in a fixed number of iterations. The iterative search for optimal solutions will stop when certain rules are satisfied. These rules normally include: optimal or near-optimal solution is found; there are too many iterations; the scalar λ_n is too small.

5.4.4 Empirical Benchmarking

In this section we give some empirical results in order to compare the new approach to optimal winner determination based on the integer programming formulation of the bid analysis problem (and consequently solved with commercial software CPLEX).

Table 5.2 Average Solution Quality of Lagrangian heuristic for WDP

Case Index	1	2	3	4	5
Carrier size	5	5	10	10	15
Lane size	10	15	15	20	25
Package size	30	40	50	60	75
Lower / Upper	.89	.88	.82	.80	.79
Upper / CPLEX	1.05	1.12	1.09	1.17	1.0
CPLEX time	0.5	0.7	1.2	2.8	2.9
Lagrangian time	0.1	0.4	0.6	1.5	2.7

Table 5.3 Average Solution Quality of Lagrangian heuristic for VWDP

Case Index	1	2	3	4	5
Carrier size	5	10	10	10	15
Lane size	10	15	15	20	25
Package size	30	40	50	60	75
Lower / Upper	.930	.874	.862	.860	.860
Upper / CPLEX	1.0	1.10	1.0	1.05	1.04
CPLEX time	0.47	1.02	1.2	1.47	1.91
Lagrangian time	0.41	1.53	1.6	1.9	1.98

The results in Tables 5.2 and Tables 5.3 are promising but in some cases we obtain

very tight bounds and in others we do not. The gap between the lower bound and upper bound solution given by the Lagrangian based method is not very tight for both WDP and VWDP. The upper bounds we generated are within 10% of the CPLEX optimal solution, which clearly shows that based on the lagrangian information feasible solutions close to optimality can be achieved. The computation time used by CPLEX commercial solver is also similar to the lagrangian heuristic.

Our results indicate that WDP and VWDP do not provide good solutions with stand-alone lagrangian heuristic. Chu and Beasley (1996) provide a genetic algorithm based heuristic algorithm for set partitioning, which performs poorly when compared with commercial integer programming solver CPLEX. In fact, Krueken, Fleurian and Peeters (2004) show that a lagrangian relaxation based lower bound in branch and bound scheme solves in less time than a linear programming based lower bound. In this chapter, though the duality gap is not tight, we provide a simple primal lagrangian dual heuristic which looks promising to be used in a branch and bound framework for combinatorial auctions with min-max carriers.

5.5 WINNER DETERMINATION WITH COVERAGE CONSTRAINTS

In this section we consider those shipper's business constraints as discussed in Caplice and Sheffi (2003): maximum / minimum number of winning carriers, incumbent preference, maximum / minimum coverage. In our analysis, several assumptions are made without loss of generality. First, we assume that the freight volume on each lane is not separable. Further, XOR bids are not considered and the bidding vocabulary is OR bid only. Ledyard et al (2002) noticed in practice carriers can easily transfer XOR

bids into OR bids by adding a lane with small value into both XOR bids.

Now, the bid analysis problem in combinatorial transportation procurement auctions is modelled as:

BAP

$$\min \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k$$

s.t.

$$\sum_k \sum_j a_{kj}^i x_{kj} = 1, \quad \forall i \quad (42)$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (43)$$

$$T_{\min}^k y_k \leq \sum_j \sum_i a_{kj}^i x_{kj} \leq T_{\max}^k y_k, \quad \forall k \quad (44)$$

$$y_k, x_{kj} \in (0,1) \quad (45)$$

In this model we have $T_{\max}^k \geq T_{\min}^k \geq 1$ and $K_{\max} > K_{\min} \geq 1$. Also note that without constraint (43), (44) and the penalty cost, this BAP problem reduces to a Set Partitioning problem which is well known to be NP-complete (Balas and Padberg, 1976).

The objective function of this formulation minimizes total procurement costs including the actual “bid” price and the penalty cost. The first constraint ensures each lane can only be assigned to one package. Constraint (43) limits the number of winners that shippers want to have in their core carrier base. Constraint (44) models the coverage constraint which restricts the number of lanes (amount of traffic) that a carrier can win

and is also the coupling constraint between x_{kj} and y_k :

$$y_k = \begin{cases} 1, & \text{if and only if } \sum_j x_{kj} \geq 1 \\ 0, & \text{otherwise} \end{cases} \quad (46)$$

Further, note that each bid package is not defined by shippers; instead, they are constructed and submitted by individual carriers themselves. As a result, different packages may be inclusive of common lanes.

Lemma 5.5 : BAP is NP-hard.

Proof:

Combinatorial reverse auction consists of objective function without the penalty terms with constraints (42) and (44) is a classical weighted set partitioning problem, which is NP-hard (Balas and Padberg, 1976).

First note that if we add another redundant coupling constraint to the BAP problem:

$$x_{kj} \leq y_k \quad \forall k \in K, j \in J \quad (47)$$

By properly choosing the parameters for the maximum and minimum number of lanes to be won by a carrier, they can be relaxed so that they do not bind the set of feasible allocations. Suppose the carrier can win any number of lanes or none at all, then problem reduces to combinatorial reverse auction problem with a constraint on number of winners which is NP-hard (Sandholm and Suri, 2001). Hence BAP is also NP-hard.

5.5.1 Lagrangian Relaxation for BAP

Relax constraint (42)

The problem structure makes it natural to consider relaxing constraint (42) in the BAP formulation. Let $\mu_i \in R$ be the Lagrangian multipliers, we have:

BAP-LR1

$$\begin{aligned} \min_{x,y} \quad & \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k + \sum_i \mu_i \{ \sum_k \sum_j a_{kj}^i x_{kj} - 1 \} \\ & = \sum_k \sum_j \tilde{c}_{kj} x_{kj} + \sum_k p_k y_k - \sum_i \mu_i \end{aligned}$$

s.t.

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (48)$$

$$T_{\min}^k y_k \leq \sum_i \sum_j a_{kj}^i x_{kj} \leq T_{\max}^k y_k, \quad \forall k \quad (49)$$

$$y_k, x_{kj} \in (0,1) \quad (50)$$

where: $\tilde{c}_{kj} = c_{kj} + \sum_i \mu_i a_{kj}^i$, note \tilde{c}_{kj} can be any real number.

Relax constraint (44)

Given two Lagrangian multipliers $\lambda_k \geq 0$ and $\mu_k \geq 0$, we can rewrite BAP to the following:

BAP-LR2

$$\begin{aligned}
& \max_{\lambda, \mu} \min_{x, y} \sum_k \sum_j c_{kj} x_{kj} + \sum_k p_k y_k \\
& \quad + \sum_k \lambda_k (\sum_j \sum_i a_{kj}^i x_{kj} - T_{\max}^k y_k) + \sum_k \mu_k (T_{\min}^k y_k - \sum_j \sum_i a_{kj}^i x_{kj}) \\
& = \max_{\lambda, \mu} \min_{x, y} \sum_k \sum_j (c_{kj} + \sum_i a_{kj}^i \lambda_k - \sum_i a_{kj}^i \mu_k) x_{kj} \\
& \quad + \sum_k (p_k - \lambda_k T_{\max}^k + \mu_k T_{\min}^k) y_k
\end{aligned}$$

s.t.

$$\sum_k \sum_j a_{kj}^i x_{kj} = 1, \quad \forall i \in L \quad (51)$$

$$K_{\min} \leq \sum_k y_k \leq K_{\max} \quad (52)$$

$$y_k, x_{kj} \in (0, 1) \quad (53)$$

The choice of constraints to relax depends on the complicating constraints shown in formulations BAP-LR1 and BAP-LR2. The next step is to decide which formulation to use to present the lagrangian heuristic and this can be decided by finding whether these formulations satisfy the integrality property (IP).

Proposition 2: BAP-LR1 does not satisfy the integrality property.

Proof:

The problem BAP-LR1 decomposes into any number of problems between kMin and kMax knapsack sub-problems. These sub-problems do not have the integrality property since the linear programming (LP) relaxation of knapsack problems does not always have integral solutions. The lagrangian relaxation (LR) scheme hence in this case yields a stronger bound than the LP bound. Also finding an LP bound is cumbersome. BAP-LR2 satisfies the integrality property. Therefore we begin our analysis of the

suitability of Lagrangian relaxation for this problem using the BAP-LR1 formulation.

The Lagrangian relaxation algorithm is generalized as this: first, given a specific μ_i , we find an optimal solution for the BAP-LR1 problem; then we search for a feasible solution for the original bid analysis problem from this optimal solution; next we examine whether the stopping rule is satisfied, if not, we update μ_i and continue this procedure to improve the lower bound.

Finding an optimal solution for a relaxed Lagrangian problem

To solve this relaxed problem, suppose for each carrier we can find a list of packages J_k^* such that $\sum_j \widetilde{c}_{kj} x_{kj}$ can be minimized while satisfying constraint (9) (we call it volume

constraint), now we compute $\widetilde{p}_k + \sum_j \{\widetilde{c}_{kj} \mid j \in J_k^*\}$ for each k and make a list out of them.

Then we select K_{\min} number of carriers from the decreasing order of the list. If there are

still carriers in the remaining of that list such that $\widetilde{p}_k + \sum_j \{\widetilde{c}_{kj} \mid j \in J_k^*\} < 0$, then we

continue adding those carriers as long as the constraint $\sum_k y_k \leq K_{\max}$ is satisfied.

For x_{kj} , we set $x_{kj} = 1$ only for those lanes that are already picked by carriers in the last step, that is $x_{kj} = 1, \forall j \in J_k^*$.

Now we discuss how to find those packages in J_k^* . We transform this problem into two Knapsack sub-problems. The Knapsack problem is still NP-complete but many efficient pseudo polynomial algorithms are known (Martello and Toth, 1990).

First note when $\widetilde{c}_{kj} \leq 0$, we should continue to add package j into J_k^* for each carrier as long as the number of lanes assigned to this carrier $T_k = \sum_{i,j} a_{kj}^i x_{kj} \leq T_{\max}^k$. For the second sub problem, if T_k is still less than T_{\min}^k after all packages with $\widetilde{c}_{kj} \leq 0$ are added, we have to select from packages with $\widetilde{c}_{kj} > 0$ and add them into J_k^* until $T^k \geq T_{\min}^k$.

For the first sub problem, let $f_j^- = \widetilde{c}_{kj} \mid \widetilde{c}_{kj} \leq 0$ and weight $w_j = \sum_i a_{kj}^i x_{kj}$ (this weight is actually the number of lanes contained in that package), the problem is to put as many packages as possible to a knapsack while the total weight satisfies that knapsack's capacity constraint T_{\max}^k . That is:

KP1

$$\begin{aligned}
 & \min \sum_{j \in J} f_j^- z_j \\
 & \text{s.t.} \quad \sum_j w_j z_j \leq T_{\max}^k \\
 & \quad \quad z_j \in (0,1)
 \end{aligned} \tag{54}$$

Note $f_j^- \in R^-$ and $w_j \in N^+$. If we rewrite the objective function in KP1 as $\max \sum_{j \in J} (-f_j^-) z_j$, it becomes a standard form of a binary Knapsack problem.

After we solve the first sub problem, we count whether the number of lanes T_k is equal to or greater than lower bound T_{\min}^k . If it is, we stop here and the optimal solution is found. Otherwise, we continue to solve the second sub problem.

Let $f_j^+ = \widetilde{c}_{kj} \mid \widetilde{c}_{kj} > 0$, the second sub problem can be written as:

KP2

$$\begin{aligned} \min \quad & \sum_{j \in J} f_j^+ z_j \\ \text{s.t.} \quad & \sum_j w_j z_j \geq T_{\min}^k - T_k \\ & z_j \in (0,1) \end{aligned} \tag{55}$$

This is a minimization version of the binary Knapsack problem. We can easily change it to a standard maximization version by letting $\bar{z}_j = 1 - z_j$.

KP3

$$\begin{aligned} \max \quad & \sum_{j \in J} f_j^+ \bar{z}_j \\ \text{s.t.} \quad & \sum_j w_j \bar{z}_j \leq \min\{\sum_j w_j - T_{\min}^k + T_k, T_{\max}^k\} \\ & \bar{z}_j \in (0,1) \end{aligned} \tag{56}$$

After we find a list of candidate packages for each carrier by solving these Knapsack problems, we can solve the relaxed Lagrangian problem easily by following procedures described at the beginning of this section.

Finding a feasible solution for the original bid analysis problem

We present an outline of the greedy algorithm used to find the optimal solution. The algorithm works as an adjustment heuristic in a lagrangian relaxation as at every iteration \widetilde{c}_{kj} and lagrangian multipliers μ are the input for this procedure to generate a feasible solution.

Feasible solution heuristic (\tilde{c}_{kj}, μ)

- Sort the lanes in the descending values of μ_i .
- Do until $L = \phi$
 - Pick the lane $i \in L$ with the highest μ_i .
 - Then pick the package with lane i with the lowest \tilde{c}_{kj} and making sure lane constraints are not violated.
 - Remove all the lanes from this package $j \in J$ from L . $L = L / (\forall i \in j)$
- Calculate the Upper bound.

The feasible solution obtained with this procedure provides an upper bound for the original bid analysis problem, and we can further improve the solution by iterating the above Lagrangian procedures with an update on Lagrangian multipliers. There are alternative ways to do this; among them is the well-known subgradient search method. Let $Z_n(\mu^n)$ be the optimal solution from the Lagrangian problem BAP-LR1 (lower bound) and x^n, y^n be the optimal assignment at iteration step n , and let Z_n^* be the feasible solution (upper bound), the subgradient search method starts with an initial value μ^0 for the Lagrangian multipliers and updates them over the iterations as:

$$\mu_i^{n+1} = \mu_i^n + t_n \left(\sum_k \sum_j a_{kj}^i x_{kj}^n - 1 \right) \quad (57)$$

where:

$$t_n = \frac{\lambda_n (Z_n^* - Z_n(\mu^n))}{\sum_i (\sum_k \sum_j a_{kj}^i x_{kj}^n - 1)^2} \quad (58)$$

In the above equation, λ_n is a scalar satisfying $0 < \lambda_n \leq 2$, normally we have $\lambda_0 = 2$ and it will be halved whenever $Z_n(\mu^n)$ has failed to increase in a fixed number of iterations.

The iterative search for optimal solutions will stop when certain rules are satisfied. These rules normally include: optimal or near-optimal solution is found; there are too many iterations; the scalar λ_n is too small.

5.5.2 Empirical Benchmarking

In this section we give some empirical results in order to compare the new approach to optimal winner determination based on the integer programming formulation of the bid analysis problem (and consequently solved with commercial software CPLEX).

Input data for each problem includes each carrier's bids, bid prices, penalty cost, minimum and maximum number of lanes if this carrier is a winner, minimum and maximum number of winners. In addition to the input generation presented earlier in the Chapter, each carrier has a T_{\min}^k that is uniformly distributed over $[1, 0.33*|L|]$ and T_{\max}^k is set to the number of lanes in the auction.

In our preliminary investigation to test the computational efficiency of the solution procedure, we generate test suites and apply lagrangian relaxation solution procedure. The numerical results are summarized in Table 5.4. The lower bound in numerical results is the best lower bound obtained by solving the lagrangian dual BAP-LR1. The

upper bound is found using the greedy algorithm presented above. The tables also list the optimal solution and time by commercial software CPLEX.

Table 5.4 Average Solution Quality of Lagrangian heuristic for BAP

Case Index	1	2	3	4	5
Carrier size	5	10	10	10	15
Lane size	10	15	15	20	25
Package size	30	40	50	60	75
Lower / Upper	.98	.90	.875	.860	.84
Upper / CPLEX	1.0	1.01	1.0	1.05	1.0
CPLEX time	0.58	1.08	1.50	1.61	1.98
Lagrangian time	0.27	1.27	6.88	9.88	12.98

From the table we can see that the duality gaps around 15%. The important thing is that we get good upper bounds, which are very close to the optimal solution. CPLEX generates optimal solutions in times less than the lagrangian heuristic does. In our experiments with combinatorial auction problems, we note that the upper bounds generated are close to the optimal within the first ten iterations of the lagrangian heuristic.

CHAPTER 6 BIDDING IN AUCTIONS

In this chapter we review bidding models for freight transportation procurement in long-term transportation auctions. We survey the current literature on bidding in transportation auctions and present a new framework for the consideration of bidding in truckload markets. We consider strategic issues in bidding and develop formulations for these situations. We extend work related to bidding on lanes to more realistic and complex volume based contracts.

6.1 INTRODUCTION

The main actors in freight transportation procurement are the shippers and carriers. The problems on the shipper side in transportation auctions have been studied in detail (Caplice, 1996) but few researchers have studied the carrier side perspective. An exception is the work of Song, 2003. This is due to a number of reasons, for example, the difficult combinatorial optimization problems to be solved by the carriers and the low technical sophistication of most of the carrier industry.

Carriers face many decisions while participating in the auctions. The carrier has to price his/her service, forecast demand and supply constraints, improve vehicle utilization, and make a plan to satisfy the level of service (LOS) requirements to fulfil contractual agreements. In long-term procurement, the questions faced by the carrier are very tricky from a strategic and operational point of view. Strategically the carrier is participating in auctions with the shipper to serve loads that will occur with certain frequency. The carrier has to know which loads to bid on and the bidding price to bid on these future loads

as the load tendering of the contracts present highly complex fleet management (operational) decisions over time. The carrier has to have a clear understanding of his/her operating costs, revenues, vehicle utilization rates, empty hauls, and profit margins. Also on the other hand the driver has to be taken care that domicile constraints are met along with the typical DOT working hour regulations, as driver turnover ratio is also one of the biggest problems plaguing the truckload industry. In addition, carriers have contracts with other shippers to satisfy the agreed-upon quality and level of service requirements. The supply management (or capacity issues) might be a very big factor and he/she might lose profits just to service a load in the contract at an agreed price.

According to Caplice (1996) for truckload procurement, “In general, the cost of serving a lane is strongly affected by the probability of finding a follow-on load out of that destination. Securing a balanced network reduces the uncertainty in connection costs and can lower the carrier’s overall costs. Thus a carrier may offer a lower price for hauling a given number of loads from A to B if it also hauls loads from B to A.”

In summary, the economics of direct transportation carriers imply the following:

- A carrier’s costs for hauling on one lane of traffic are highly influenced by the remainder of its business,
- Carriers can reduce their total costs by intelligently selecting which lanes to serve and at what level of business, and
- The effect that potential businesses has on a carrier’s costs is specific to that carrier, that is, the value of the private information is more

influential than the value of the public or common information.

In the past shippers have traditionally used classic auctions for long-term contracting. As we defined in Chapter 2, freight procurement presents interdependencies among bidding items and an auction mechanism should take advantage of these synergies. In Chapter 4, we define unit auctions, where combinations of loads are grouped into packages by shippers to take advantage of the economies of scope in the shipper network. Combinatorial auction (CA) are being increasingly used in the industry especially for long-term truckload market, where the carrier can bid for a combination of loads. The combination of loads is important as it brings about economies of scope property to the carrier operations (Caplice, 1996). The complexity of these package auctions is due to evaluation of the set of loads suitable for them, the empty repositioning, dwell time issues and also the expected revenues the combinations generate. Song and Regan (2002) present optimization-based models to generate profitable load combinations for bidding in combinatorial auction with pre-existing commitments or no commitments. Caplice (1996) develops some heuristics to form packages of loads. An, Kescinocak (2005) and Wang, Xia (2004) develop a synergy based model to find out the valuation of bundles. Plummer (2003) presents the cases of carrier bidding in combinatorial auction.

In brief, following are the questions faced by the carriers while bidding in combinatorial auctions:

- Bid Construction Problem: what lanes to participate: valuations of lanes or bundles with pre-existing commitments or no commitments. Lane bundles involve synergy in terms of load balancing, business value etc. An, Kescinocak (2005) use a synergy value to find out the valuation of bundles. Song and Regan (2002) discuss optimization-based models using set covering formulations to solve them.
- Packages: Song and Regan (2002) suggest that bundling is better than singleton bids. Plummer (2003) discusses various industry used package types. An uses two strategies internal based bundling and competitive bundling. How to select bundles for bidding and which bundles to select are problems that have not been studied extensively in the existing literature.
- Pricing strategy: What to bid on the bundles? An, Kescinocak (2005) and Song, Regan (2003) say that carriers use a fixed profit margin in their pricing strategies.

Because of these problems, few carriers actually submit package bids. Usually big and sophisticated carriers having the required technical know-how submit these package bids. Forming continuous routes has been the most favored form of combinatorial bidding. Post auction it seems though the carriers tend to win the packages whose bids are never tendered. The carrier has to take into account the risk involved in such situations and what happens is that the carriers who have put in a lot of effort in making packages do not actually get benefit from these packages.

Another hindrance for carrier decision-making ability is the non-availability of a decision framework for the carriers to bid in the auctions, which incorporates robust and probabilistic tools for developing bids. Carrier bidding methodologies, which explicitly consider stochastic and dynamic nature of transportation services and as well as the ex ante probabilities of being awarded the bid are non-existent. They also need a balanced network to weed out any inefficiency like repositioning costs.

As we defined in chapter 2, we consider two forms of truckload service procurement market structures: 1) Long term 2) Short term or spot markets. In chapter 3 we discussed the bidding problems of the carriers in spot markets and this chapter explicitly focuses on the carrier bidding in long-term markets. From a carrier side, the problems involved in both the long-term contracts and short-term contracts are really different and depend on the transportation service in question. The remainder of the chapter assumes that a freight contract is made through an auction mechanism. We will exclusively focus on the truckload carriers bidding in combinatorial auctions.

6.2 LITERATURE REVIEW

In this section we focus on the literature survey of bidding models for truckload freight procurement for long-term contracting. In Table 6.1 we present a literature schema of long-term carrier bidding.

How do the truckload market work and what is the carrier's perspective involved in auctions for procurement? The most important economic concepts from a carrier's point of view are economies of scale, scope and density. Economy of density (EOD) is defined

as the increase in marginal cost by increasing shipments holding the network size and spatial size constant. According to Plummer, EOD is relatively significant in TL operations. TL carriers are more sensitive to balance of loads so have diseconomies of scale (Caplice, 1996). Balanced lanes in a network, according to Caplice are the volume of inbound freight to one destination is approximately equal to the outbound volume from that point. This is very important and controls TL economies. Hence while procuring freight, it is of vital important to look for points where the probability of getting a follow on load is more and remove deadheading, dwell time etc.

In the present freight procurement methods, many TL firms use CA auctions. For a carrier the lane valuations depend on 1) Exogenous factors, 2) lane demand structure, 3) location of nodes and 4) physical network. The other endogenous factors, which depend on carrier's operations are service structure, route structure and link sequence/operating rules. Usually the shipper's network is the primary driver of carriers' economies, but the most difficult part for carriers is to evaluate which lanes to serve and at what price to bid on the shipper's network. Though the carrier wins a set of lanes in the auction the carrier is not guaranteed to ensure steady flow of i.e. how many shipments he/she will get and where they are going.

From an operational point of view the carriers have to manage their fleet operations in such a way that profits are generated, vehicle utilization is improved, and the driver returns to his/her domicile after the planning period (usually less than two weeks). The carrier has to make sure that there is high probability of re-load availability at the destination to minimize dwell time or find a re-load close to it so that deadheads are

minimized. In all this the route structure must be designed to keeping in mind the driver working hour restrictions.

Table 6.1 Literature schema for carrier bidding in long term auctions

Authors	Research synopsis
Song, Regan	Develop optimization based bidding rules for single round combinatorial auctions. The model takes form of an operational perspective.
Lee, Kwon, Ma	Develop optimization based bidding rules for single round and multi-round combinatorial auctions
Plummer	Reviews the carrier bidding strategies (heuristics) used in real combinatorial auctions in a single round auction. No optimization framework used for transportation bidding.
An, Kescinocak	Develop a synergy model to tackle combinatorial bidding. Use auction theory concepts for bidding.
Samik, Veeramani	Apply an optimization based learning mechanism schemes for bidding multi-round auctions. Explicit focus on transportation auctions data characteristics and historical winning prices consideration.

The carrier also has to deal everyday with RFQs from various shippers and this also

adds to the complexity of fleet management. The carriers in practice only respond to a fraction of RFQs. Knowing shipper network and lane-demand structure is helpful for carrier bidding as it improves the asset utilization and helps to bid in the auctions using packages of lanes, which complement their pre-existing commitments.

The important information that the shipper needs to provide for the carrier to bid in the auctions is lane volumes, seasonal fluctuation of demands on the lanes, and shipment loading and unloading times. Once the carrier decides to bid on the lanes he/she has to decide the price to quote in the auctions. The pricing factors generally depend on operating costs, drop-trailers required, shipping times, loading and unloading, driver friendliness and shipment consistency. The operating costs involve direct costs, vehicle licensing cost, truck-to-trailer ratio, driver costs, administration costs, overhead, tolls etc. Another important metric for evaluating to bid on lanes is lane density, which is a combination of volume in lane and balance of freight between origin and destination. Usually lanes with higher density are charged lower price than lanes with lower density and large carriers use this measure to secure balance in the network.

Every node has costs: deadhead cost, dwell cost, availability of freight from this point and the literature does not consider the effect of origin, destination points while procuring. Large carriers have proprietary software to bid on lane given its impact on the balance of the network. If the probability of finding a backhaul is increased then the pricing department bids less to compensate for balancing the network and all these considerations depend on the historical deadhead, dwell time costs etc.

According to Plummer (2003), CA helps carriers balance their network but these do

not imply continuous moves. CA is a strategic tool that allows carriers to reflect true costs when securing freight volumes in unbalanced lanes. Continuous moves are an operational tool to provide a truckload carrier with a predictable freight pattern to minimize deadhead and dwell time. CA allows the carriers to create package and conditional bids to express their synergy on lanes. CA auctions have proven to provide efficient allocation and decreased threat of exposure for the bidders (de Vries and Vohra, 2002). But the downside for the carriers is that they have to solve hard optimization problems to be able to take advantage in these auctions. The bidding also has to be able to take into account the demand forecast provided by the shipper and his/her own estimates of future forecast for his/her pre-existing commitments.

The carrier can only have profitable post auction revenues if the shippers execute these packages of lanes. In practice, most shippers fail to do this and hence the carriers have to hedge against uncertainty. The shipper therefore has to be able to execute the packages for a win-win situation for both of them. In most auctions the shipper considers his/her business constraints in the auction, which also makes it very difficult for the carrier to bid in the auction.

6.2.1 Plummer

Plummer provides an in depth data analysis of combinatorial bids from real auctions. The questions he poses are:

- ❑ How do package bids look?
- ❑ Which lanes are being bundled?

- How much is the carrier discount for bundling of lanes?
- Do packages win bids?
- What factors drive the price of truckload carriers in CA?

The combinatorial auction data is taken from 13 unique auctions with 644 TL carriers, 5233 lanes, 90908 bids, and 1294 packages. From the data, approximately 30% of the bids are package bids and 30% of carriers submit package bids. From carrier interviews, the impediment to more packages is because of the uncertainty of follow up loads, the phenomenon that package bids rarely win auctions and that the shippers rarely execute the packages. Package bids reportedly reduce deadheading and dwell time, but improper execution means that dwell time is increased. He also notes that package bids add balance to network and not necessarily continuous tours.

From the data the number of packages submitted by the carriers in fact range from just two to seven and the package size was small; between two to four lanes. The one reason for predominantly small packages is the huge number of RFQs carriers face and time constraints for proper analysis and need a lot of IT resources. Large packages – some contained disparate collection of disjointed lanes with multiple origin destination points or outbound shipments from a single point to multiple destinations. Also the data showed that the package bids do not necessarily are low in cost. Data also debunked the myth that lanes with large volumes will be packaged more often.

Some of the commonly used bids are:

- Round trip/continuous moves: Round trip are usually continuous moves and they

lower probability that a carrier will have to deadhead or reduce dwell time.

- Destination packages: A group of lanes from a destination that helps to leverage existing freight coming out of the destination by offering lower rates on lanes going to that destination.
- Origin packages: Carriers having an imbalance of freight out of a region use this origin packages.
- Disparate lanes: A group of lanes, which are not linked due the adjacency of network to help the carriers achieve balance in their network at a system level.

The data also showed predominantly three types of bidding strategies:

- Small carriers: build continuous moves or conditional bids (simple round trip packages).
- Medium carriers: network optimization software bundle lanes on a regional basis. Use OD packages to leverage their existing shipments volumes and create balance within a given region. (OD packages)
- Large carriers: sophisticated software to gauge the impact of all lanes in every auction. Consider impact of each lane on the network, but also bundle unconnected lanes for balance. Large carriers submitted more packaged lanes than others. (OD packages, disparate packages)

Package discounts tend to be in the neighborhood of 5%, but in majority of cases do not give discounts. Shipper's network is the underlying key to package discounts.

Carriers believe that packages bids do not win because of shipper's own business objectives. Also some carriers who focused on small regional networks win the auctions. Hence single lane bids conditional on volumes occasionally wins. Sometimes the small carriers seek only to earn a profit threshold, and that such a carrier will lower its prices

beyond those of a profit-maximizing firm. Regional factors are very important for carriers in bidding. Cost depends on where the shipment is originating and going to. Each origin and destination represents a different probability of getting a reload. To account for this they may have to deadhead or dwell. Hence the pricing depends on the deadheading and the dwell time at these points.

6.2.2 Song, Regan

Song, Regan (2003) look at the unit contract case (all-or-nothing case), in which a lane or a set of lanes are allocated entirely to a carrier, and call it the bid construction problem. They analyze the impact of CA in transportation freight procurement and compare the CA auctions using conventional methods with a simulation-based analysis. Later they tackle the CA bidding problem for carriers and study how much benefits of CA auctions to each carrier.

The bid construction problem may be even harder in the procurement of freight transportation contracts. Song and Regan (2003a) pointed out that in the worst case a bidder or carrier must solve an exponential number of sub problems to identify their reservation prices and that each of these sub problems is NP-hard. In the trucking industry, carriers not only need to consider the economies of scope exhibited in delivery routes from new contracts, they also have to find an efficient way to integrate new contracts with their pre-existing commitments. This problem normally modeled as a vehicle routing problem, is itself NP-hard in most cases as its solution typically requires the solution of variants of multiple traveling salesman problems.

The authors tackle the following questions: How to identify the most profitable subsets of bidding items? How should carriers determine their true value for a particular bundle of new contracts? What is the optimal way to structure different combinations? These questions are not easy to answer even for simple cases. In fact, bidders might encounter much more complex optimization and decision problems than do auctioneers in a combinatorial auction.

For combinatorial auctions the authors propose to solve a Vehicle routing problem (VRP). The objective function minimizes the total operating cost or total empty movement cost, and the first constraint set guarantees that every lane (either current or new) will be covered exactly once. They propose to find a set of periodic routes of lanes and solve a VRP. Carriers have pre-existing commitments for a set of current lanes and to satisfy this new demand they have to form packages such that they can have the economies of scope. In this every point has a probability of getting a backhaul lane that has not been used to model in the optimization process. The onus is on the carrier to evaluate the proprietary information, common information, and a mixture of these affiliated signals.

The formulation, given a set of lanes U and a new set of lanes V , the reserve bidding price for this new set can be calculated using a set partitioning algorithm. From this point onwards we will term the formulations by Song, Regan as SR formulation. This is a single sourcing constrained system and the shipper might want a multi-sourcing environment:

$$\begin{aligned}
& \min \quad \sum_{j=1}^n c_j x_j \\
& \text{s.t.} \\
& \sum a_{ij} x_j = 1 \quad \forall i \in U \cup V \quad (1)
\end{aligned}$$

$$x_j = 0,1 \quad (2)$$

Where $j = 1, \dots, n$ is the index of valid cycles; c_j is the cost to operate cycle j ; x_j is a binary variable indicating whether cycle j is in the optimal allocation; and a_{ij} is a binary coefficient which indicates whether lane i is included in cycle j . These cycles include either current lanes or new lanes purely or a combination of new and current lanes and should satisfy all operational constraints, further, note that each cycle's operating cost can be replaced by its empty movement cost. The objective function minimizes the total operating cost or total empty movement cost, and the first constraint set guarantees that every lane (either current or new) will be covered exactly once.

In the SR formulation, the authors do not consider factors like revenue from the cycles, repositioning costs, shipper execution, probability of demands actually coming up, volume considerations based on lane demand structure. Only the operating costs are explicitly considered in the formulation. The solution, though, will give the best allocation of lanes that will fit with the present new lanes in the carrier's business. They bid an all or nothing bid and talk about the implications of these bidding language in dealing with combinatorial auctions. The formulation uses an XOR bidding language based on building blocks of atomic bids. For a thorough introduction to bidding

languages in CA, the readers are referred to Nisan (2000). Bidding languages: helps to communicate the bids. need OR, XOR and conditional bids. Atomic bids in transportation auctions can take different formats based on length of the lane, volumes on each lane etc. (Caplice, Sheffi, 2006).

A simulation scheme is set up to compare the effectiveness of single shot closed combinatorial auctions against the first price sealed bid lane-by-lane auction. Development of packages depend on the form of the auctions: in a first lane auction the carriers see if there is a marginal benefit of including the lane in the auction and bid that true valuation. Bid construction search algorithm scans or deletes all full cycles consisting of two or three links with a mixture of current and new lanes. Next step is to scan all partial cycles with empty movements and make bids accordingly. Song and Regan (2003) use the following formula to calculate the bidding price P for new lane(s) in an atomic bid using the formula:

$$p = c_i \times (1 + \beta) + c_j \times \alpha_j \quad (3)$$

Where c_i is the total cost of serving the new lane(s) in that atomic bid; c_j is the empty cost associated with serving those lanes; β is the carrier's average profit margin, which typically ranges from 4% to 6%; and, α_j is the carrier's risk of not tendering any future demand on those empty lanes j . Since normally a carrier's cost is proportional to distance, the authors use distance to represent cost. In the simulation, bid winner determination solved using a set-partitioning problem presented above. The metrics used

for evaluation of these auction mechanisms from a carrier's perspective are maximum expected profits and more market share.

From the simulation results they find that the shipper's average cost reduction is increasing with increasing density of new lanes. The reason being as the density of loads increase procurement costs are reduced as we have more opportunities for backhauling. Shipper's average cost reduction is decreasing first and then increasing with increasing density of current lanes. Carrier's average empty cost reduction is increasing under increasing density of new lanes. The empty cost reduction for the carrier also is like the shipper's for different density of current lanes. Shippers and carriers cost reduction is related to the distribution and density of new lanes, in addition to current lanes. The results are only for the case of unit demand for each lane; the authors expect more efficiency (or gains) for multiple lane demands.

The author's focus on the bid construction problem is to identify the carrier's true cost valuation for a cluster of demand. The carrier's bidding problem is a hard one as bid valuations have to consider exponential number of combinations and also formulate a logical relationship with the individual elements in the bids. Here they present an optimization-based strategy for carriers to construct optimal or near optimal bids by solving NP-hard problems (with pre-existing or without pre-existing commitments). Even in a collusion-free environment the bidders need to figure out which combinations to bid and what reserve price to bid on. The other constraints include assigning and balancing their vehicle resources with pre-existing or without pre-existing commitments. Time is also a factor in deciding quickly what bids should we bid on. SR model consider no

central depot and assume capacitated carriers. Carriers do not consider future demands during the auction period. Unit contracts used here to bid in the auctions and with out any reference to the amount of volumes on these bids. The authors develop a methodology to find out various complementary and substitution effects between current commitments and lanes under bidding. They also assume carriers do not know other peoples bidding strategy or attempt to compute their valuations implying that competition is ignored and bidding is based on private values only. We will present the formulations by Song and Regan later in the chapter, as we will build our formulations using them as the basis.

6.2.3 Samik, Veeramani

Samik and Veeramani (2005), discuss the use bid determination method for carriers in single lane and CA auctions in successive (multiple round) auctions to maximize profits. From their personal communications with carriers, the authors contend that for truckload, flatbed or refrigerated fleets are multiple rounds and one round is usually market price discovery round and LTL auctions are usually one round and with a negotiation phase which can be a multi-round format. The process involves selecting best bid at each round of CA auction using adaptive bidding using concepts from Bayesian game theory. They compute a profit factor at each round using the industry average price for a lane or a bundle using historical values and using these they select the best set of bundles to bid to maximize the expected profit of the carrier.

Learning algorithms is the core of their thesis. Carriers can develop a model-based bidding based on previous experience. Carriers can use adaptive learning or direct

learning (bid your own utilities). The bidding model then involves solving a mixed integer programming formulation, which uses the capacity of the carrier, perceived importance of a lane and also captures the probability of winning (a measure of risk) associated with the bundles.

Model for single lane bids

Samik and Veeramani (2005) develop a profit factor based approach basing on the concepts from Bayesian game theory to generate profit factors for each carrier. In their model, carriers compete for L lanes with other N carriers. Assuming the rationality of bidders, bid $b_{il} = f_{ilk} c_{il}$ assuming rational bidders, where f_{ilk} multiplier, for bidder i for lane l , auction round k . A minimum rounds R_{\min} and R_{\max} are assumed to be present and as decided by the shipper while designing the auction format. Risk behavior modeled by p_{il}^{\min} and p_{il}^{\max} based on historical results of previous auctions for the bundles.

The algorithm for single lane bids is as follows:

- Find mean and SD of winning price for each lane. Find true costs c_{il} and multiplier factor f_{ilk}
- Round Index $< R_{\min}$, if she won don't change the bid else reduce by minimum decrement or retain if she has already reached her cost.
- Rounds Index $= R_{\max}$: here the carrier bids no what if he won the auction or not. Find the mean based on rounds until now.

Updating the means and SD to calculate the profit factor is what differentiates each carrier from one another. The means are updated using a maximum likelihood

estimator and also another method to weigh the winning bids of the previous rounds, which depends on the historical winning price of that lane. Profit factors are calculated using the Bayesian game theory techniques and the updated means using maximum likelihood estimation at every iteration of the auction.

Model for combinatorial bids

The authors develop a mixed integer-programming model for bid selection in combinatorial auctions while considering capacities explicitly for a tactical level of planning. Song and Regan's formulation (2003) can be used for operational level analysis.

$$\max \sum_{b \in B} c_b (f_b - 1) p_b y_b$$

s.t.

$$\sum_{ij \in L} (l_{ij} + l'_{ij}) x_{ij} \leq cuW \quad (4)$$

$$\sum_{b: ij \in b} p_b y_b \geq \hat{p}_{ij} \quad \forall ij \in L \quad (5)$$

$$x_{ij} \geq y_b \quad \forall ij \in L, b \in B \quad (6)$$

$$x_{ij} \in \{0,1\} \quad \forall ij \in L, \quad y_b \in \{0,1\} \quad \forall b \in B \quad (7)$$

where :

c_b - cost for package b

f_b - profit factor for bundle b

p_b - probability of winning bundle b

l_{ij} - flow commitment lane between i and j

\hat{l}_{ij} - pre-existing flow commitment between i and j

x_{ij} - amount of flow from i to j

\hat{p}_{ij} - assumed probability of winning for lane $i \rightarrow j$

y_b - if bundle b is chosen ij

L - number of lanes in the network

B - the set of all bundles

c - is the percentage of overbooking

W - total number of trucks in the network.

u - utilization factor

The authors maximize the probability of winning the bundles of lanes. Again the model is an all or nothing model and it does not tackle the multiple sourcing cases. Other constraints include: the capacity constraints, lane importance constraints used to rectify the imbalances in the network, and the lane-bundle coupling constraint, which is an important consideration our model too.

Samik, Veeramani (2005) and Lee, Kwon and Ma (2004) present formulations for analysis at the strategic level. The authors do not use auction theory and also demand and supply contingencies, which are of huge importance for carrier bidding. The CA bidding model is presented for a multi-round auction format and the adaptive bidding strategies suggested are similar to the model presented for single lane auction but the carriers have

to solve the mixed integer program at every round of the auction. The lane importance constraints to model flow imbalances and the authors suggest a column generation method to solve the ensuing integer program.

The model does not consider hedging due to demand and execution constraints are not considered here explicitly. The authors also do not provide a deep network based understanding of how to combine the lanes to form bundles and also the pricing mechanism used for bidding.

6.2.4 An, Kescinocak

An and Kescinocak (2005) discuss a synergy model for general combinatorial auctions and claim to be the first synergy based model for bidding in combinatorial auctions. Wang and Xia (2004) develop a synergy for transportation auctions based on empty hauls. Two items in an auction are said to have synergy if their combined value is greater than the sum of their independent values. For example lanes in a transportation network may complement each other like having a back-haul or continuous move.

The authors assume that the bidders do not have the necessary technology to create bundle bids and manage their complexity. The paper focuses on single round CA and the authors propose a simple model to evaluate the value of bundle based on the synergies, design bidding strategies that efficiently identify desirable bundles, evaluate the bundling strategies in different market situations. For a singleton bid, the bundle value is the item value. For a doubleton bid the synergy is the sum of the two item values plus the pair

wise synergies. The authors do not provide a way to calculate the synergy of the items.

The authors provide a simulation-based analysis to test the effectiveness of three bundling strategies a) naïve - singleton bids, b) internal based strategy – based on the relative value of the shippers lane relative to their own network rather than the competitors, c) competition based strategy – in this they take into account the competitors item values is it a common value assumption. Competition based strategy is a mixture of common value and private value model but still a good approximation we can use the common value model. The authors only look at the problem of bundling lanes and not the pricing issue. The prices are multiplied with a profit margin for simplicity. The five common bidding strategies the authors use for simulation analysis: 1) singleton bids 2) bid on high value packages 3) competitive bids (taking into account competition while generating the packages, 4) combine attractive lanes with less attractive ones, 5) packaging lanes to increase the density of lanes in the area.

The authors study the following problems using a simulation methodology:

- Auctioneer's revenue impact as the number of bundles increase
- Revenue distribution between CA with non-CA auctions
- Relationship between bidder's size and the efficacy of a particular bidding strategy
- The critical and non-critical factors in determining the performance of the bundling strategy
- Relationship between bidder's size and optimal profit margin

They perform auction on transportation lanes and spectrum locations. Transportation auctions are considered with 4 regions and 20 items 5 bidding items for each region. They also put a limit on the number bid packages allowed for each bidder. Experiments showed large benefits for both bidders and auctioneer in bundle bids. Simple bid rules were suggested but the results are directly not transferable to a carrier's network optimization point of view. The synergy values generated and the estimation of the valuations of the competitors were not clearly explained. The model also does not tackle pricing issues in CA.

6.2.5 Lee, Kwon

Lee, Kwon and Ma (2004) develop a carrier bidding model for CA. The authors also do not consider lane balancing in their formulations. The authors consider carrier capacity issues with a center depot, and pre-existing commitments. The objective is to find new lanes such that they fit well with existing business for repositioning, operational costs and revenue generation. The formulation is static, doesn't take into account the probability of winning in these auctions, and hedging is not considered.

The formulation contains only cycles or cycles with sub-tours, which the carriers do not actually want in practice in long-term procurement (Plummer, 2003). The formulation is integer-programming formulation with non-linear objective function and non-linear constraints. Other constraints are: tour length restriction constraints, capacity restrictions, pre-existing demand satisfaction constraints, restriction that the tours start from the depot, node selection constraint (as in this formulation we do not assume that the paths are

given, but rather determine them by solving the formulation).

The model is more suitable for a multi-round auction in that the prices for bidding are obtained from the pricing problem of WDP. The formulation is a maximization of profits i.e. revenues minus the physical costs. The formulation generates routes and also the volume of truckloads that have to be bid on these lanes. Song and Regan (2002) methodology has two phases: path generation and then selection of these routes. The authors here provide a formulation that solves the two phases simultaneously. They solve the cumbersome formulation using column generation and lagrangian relaxation methods. The bounds presented are not tight and requires a lot of computational complexity. As Wang and Mia (2004) show that a heuristic performs relatively similar to an optimal solution ex post in their simulations for carrier bidding policies, the model therefore is might not be helpful. The time taken for the problems to solve are relatively high and also do not really reflect the practical aspects of procurement bidding.

In Kwon, Lee (2006), the authors use this optimal bidding strategy in a multi-round auction scheme, thereby developing an integrated carrier bidding and shipper WDP solution procedure. This methodology is actually of limited applicability, as it does not consider shipper's business constraints.

6.2.6 Wang, Xia

In this paper, Wang and Xia (2004) define the bid generation problem and clarify the optimality criterion. They also provide simulations to test whether bundles generated by a heuristic or an optimal truck routing problem provides better results. The authors define a

bid based on the intuition from set theory. The authors define the bidding languages and focus only on the OR bids as the bids generated from an optimal truck routing problem would consist of only complementary items. The authors define first order and second synergy with respect to transportation auctions. The authors formulation considers all the combinations and also giving an analysis of ex ante and ex post differences of the final allocation.

The authors use value based pricing, defined as the market price based on supply-demand characteristics. Cost pricing is something defined based on profit margins. Under value based pricing we can safely ignore the revenue maximizing formulation and try to see how we can decrease our operating costs as for each carrier, if he wins the price he receives from the shipper is the same. The authors argue that combinatorial auction can be used for spot markets, but to be successful development of good routing heuristics need to be developed.

6.3 BIDDING FOR TRUCKLOAD CARRIERS

In this section we focus on carriers involved in a long-term auction mechanisms. In long-term contracts the freight procurement process is a strategic/tactical issue and in a spot market the procurement is a purely tactical/operational issue. We described briefly in Chapter 1, the activities in a bidding process. For the purpose of simplicity and ease of computation, we define two kinds of contract mechanisms:

- Unit contracts: In this the carrier bids for the right to serve all the

demand on a particular lane. This models the single sourcing case. The development of unit contracts is a relatively simple problem in CA as the bid evaluation depends on which lanes to mix and at what price.

- Volume contracts: In this the carrier bids for only a part of the demand on each lane and models the multiple sourcing case. Volume based contracts bring in the added complexity of restricting volumes on each lane in a bid on top of lane bundling.

Song and Regan (2002) present formulations for unit contracts, i.e. single sourcing contracts. In this thesis we will first examine unit contracts and then provide formulations for volume based contracts.

We explored numerous factors that impact carrier bidding. As it is not possible to study all those factors without having realistic data, we develop our formulations on two main considerations for the carriers while bidding in auctions: i) Revenue generation for each lane or bundle and ii) System balance constraints. For carrier's bidding in auctions, bidding is also dependent on the information available to them. Optimal bidding strategy in these auctions depend on the following attributes of information:

Table 6.2 Information structure in long term auctions

Information	Attributes
Carrier proprietary information	<ul style="list-style-type: none"> ❑ Valuation of each lane ❑ Bundling of lanes ❑ Bundle valuations ❑ Bundle pricing ❑ Pre-existing commitments
Common information:	<ul style="list-style-type: none"> ❑ Auction mechanisms details ❑ Bidder's risk taking behavior ❑ Lane demand structure ❑ Price distributions ❑ Node dynamics (regional potentials etc.) ❑ Stochasticity of demand and supply ❑ Historical data of auctions
Unknown information:	<ul style="list-style-type: none"> ❑ Carrier's competitors private information ❑ Demand/supply uncertainty over the period of contract length

The carrier's look for synergies in transportation lanes to take into account the cost interdependency by forming complementary and substitution bids. For a mathematical treatment of bids and bidding language for CA in truckload procurement, the reader is referred to Song and Regan (2003) and Wang, Xia (2004). The cost of valuation or reservation value for each lane is really important. Reservation value is defined as

the lowest amount that the carrier is willing to ask the shipper to serve the lane. The value of a traffic lane is often uncertain, and also an accurate valuation can require that an agent solve a hard optimization problem. In truckload operations reservation values are actually random variables. For our formulations, we will assume that the carriers have two components for reservation value: operational – cost of hauling (line haul and repositioning) and strategic – profit margin for the lane (Caplice, 1996). Operational factors reflect the true economies of the carrier and they are impacted by shipper's network, spatial and temporal distribution of the loads and empty repositioning. Strategic factors depend on the behavior of other carriers in the auction and shipper's business credibility. The system balance constraint helps the carrier to improve vehicle utilization and reduce driver turnover ratio. Without pre-existing commitments, the main focus of the carrier is to bid on the lanes such that network balance is achieved while bidding on the shipper's lanes. With pre-existing commitments along with system balance, bid evaluation depends on these pre-existing contracts.

The other important factor is the use of non-price business constraints in long-term contracts to solve the winner determination problems (WDP). Sometimes a carrier might put in a lot of effort and in the end win nothing in the auction. The chief auction mechanisms we will look into are the multiple unit auctions without package bidding and the combinatorial auctions with package bidding.

6.3.1 Literature shortcomings

Bidding in CA auctions is a heuristic process. The inclusion of the variables affecting the final award of the process is too complex to be solved in a single optimization

model. The research presented above tries to tackle different issues to improve bidding in long-term auctions. We discuss some of the shortcomings of the literature in carrier bidding:

- **Tactical level of planning:** Most of the models consider only operational level of details. This is due to the fact in truckload transportation though the carrier has a contract to serve a lane, the service is provided as and when the loads arise. Usually models consider a weekly pattern of demands and based on these weekly demands bid in the auctions. It is very difficult to predict the shipment forecast as well the capacity forecasts.
- **Single sourcing and multiple constraints:** The models in literature only consider unit contracts i.e. single sourcing constraints. The models bid on lanes and multiple sourcing considerations i.e. bidding on lane or package volumes are not considered. The models for the development of conditional bids are also lacking, as the packages are usually a set of lanes, which form a tour.
- **Carrier competitive behavior:** auction theory rules and strategic competition has not been looked deeply into using network optimization. Hedging rules and demands satisfaction rules for combinatorial bids too are not considered.
- **Follow on load uncertainty:** While developing continuous tours, analytical methods to estimate the probability for follow on loads to actually occur are not explicitly considered. Caplice (1996) provides some insights to deal with this problem.
- **Pricing issues:** Until now a profit based pricing is the only scheme that has been looked into. The effect of node potentials i.e. taking pricing factors where the probability of getting loads from a particular point of the follow-on loads do not occur are not considered.
- **System balance:** Carriers need a balanced network that reduces the uncertainty in connection costs and can lower the carrier's overall costs. Formulations presented

in literature do not include system balance constraints.

- **Probability of the actual award:** The incorporation of the probability of actually winning the award in the auction based on historical winning bids has not been looked into.
- **Impact of shipper's business constraints:** In most cases shippers use their non-price business constraints while determining the award allocation. The carrier bidding strategies have to take these things into account. The effects of incumbency, coverage constraints and minimum-maximum carriers constraints have to be looked into.

6.3.2 Individual Lane Pricing

We present a method to take into account the cost interdependency and the uncertainty of getting follow-on loads using a pricing scheme. The method here is to take into account the uncertainty of follow-on connectivity when determining the value or price for each shipment.

Total system contribution of each shipment hauled for a given type of equipment in a given time frame:

$$\pi(q, i, j) = R(q, i, j) - D(i, j) + P(q, j) - P(q, i) \quad (8)$$

where:

$P(q, j)$ = extra contribution of the extra truck carrying a shipment at region j . This can be also called the potential of the region.

Hence carriers should agree to haul a load if only this system contribution is greater than

zero. If $P(q, j)$ is high enough then we can move the truck from i to j without charging any cost. This called a repositioning move. $D(i, j)$ – is the common value term in auction terms. $P(q, j)$, $P(q, i)$ also imbed the common values as the regional potentials are quite well known. These regional potentials aid the process of real time decision-making about dispatching trucks or spot market pricing. Regional potentials capture to an extent the costs related to the uncertainty of incurring deadhead miles or dwell time at a shipper’s facility.

6.4 UNIT CONTRACTS

In unit contracts the carrier bids for the right serve the entire demand on a lane for the length of the contract period. The basic assumption is that the carrier has sufficient capacity and winning the lane helps in defining periodic routing plans especially for lanes with high volumes.

From an operational perspective the carrier bidding problem can be described as in Song and Regan (2003).

SR model:

Min. total empty cost

s.t.:

each load is served once; (9)

each load is contained in one cycle; (10)

flow conservation constraints; (11)

other operational constraints; (12)

Lee, Kwon, Ma (2004) consider maximizing the total utility instead of minimizing total empty cost. But their approach requires ex-ante consideration, in the sense that the probability of the lanes actually winning in the auction is not considered. A more realistic model would consider the likelihood of winning each lane and hence maximize the expected utility of the auction process. The formulation must be robust in nature, taking into consideration the demand and supply side stochasticities and other exogenous factors like demand uncertainty, re-load shipment, shipper side constraints, etc.

Proposition 6.1: In the auction model the carrier tends to maximize the expected ex ante revenues from the auction procedure.

For the sake of notation, we will denote this model the NR model (in contrast to the earlier SR model);

NR model:

Max. total expected utility

s.t.:

each lane is served by one package; (13)

flow balance constraints; (14)

demand and supply stochasticity; (15)

other operational constraints; (16)

The objective is to find the best assignment of bids with maximum utility to the carriers subject to the constraints that each lane is included in one package, flow

conservation is maintained and operational constraints are satisfied. These operational constraints include, but are not limited to, the maximum cycle length or scheduling constraints. In these models we assume fixed routes, which helps carriers to control driver turnover and also assists with driver route compliance. Most of the companies use such routes to ensure that drivers have equitable work shares (Hall et. al 2002).

6.4.1 Operational NR Model

We present a carrier-bidding model for unit contracts with and without pre-existing commitments. The strategy to generate bids for carriers in which combinational bids consisting of bundles of new lanes are favored against single-item bids in which each bid only contains a single new lane. The idea is straightforward: we make carriers generate bids in such a way that the total expected revenues are maximized.

The first step of this strategy involves using an exhaustive search algorithm to enumerate all routes with respect to routing and time window constraints and treat each of them as a decision variable in the set partitioning type formulation. For example, a depth first search algorithm can be applied to find routes satisfying the following constraints:

1. A route does not visit one location more than once;
2. If time windows are considered, a lane's delivery schedule has to match the subsequent lane's pick-up time; Note that in general, the lanes do not have associated time windows.
3. No two empty lanes can occur consecutively in a route (these would be replaced by a single direct empty move);
4. Other operational constraints such as maximum route distance or driver work

rules may be applied.

In this process each new lane is duplicated first such that it can be also used as an empty lane by other routes. And each route constitutes a candidate bid $y_j \in J$: the new lanes in this route form the set of bidding items and its reservation value can be calculated based on route length, empty movement cost and a carrier's profit margin (Song and Regan, 2003). We associate an empty movement cost e_j with each bid y_j that is equal to total empty cost of that route.

NR model

$$\text{Max} \quad \sum_{j=1}^J p_j f_j y_j$$

s.t.

$$\sum_{j=1}^J a_{ij} y_j \geq u_i \quad \forall i \in I \quad (17)$$

$$\sum_{j=1}^J y_j \leq W \quad (18)$$

$$y_j \in Z^+ \quad (19)$$

where:

$a_{ij} = 1$ if lane i is included in tour j

$u_i = 1$ for lane i without pre-existing commitments

p_j - profit to serve tour $j \in J$

f_j - probability of winning the right to serve tour $j \in J$ in the auction

$p_j = b_j - c_j$

b_j - bid price for tour $j \in J$

c_j - carrier cost for tour $j \in J$

W - capacity of the carrier

In the formulation y_j is an integer decision variable or candidate bid in set J . If a lane involves multiple loads, y_j is an integer instead; i is a new lane in set I , and u_i is the number of loads on that lane. Note the number of possible routes is exponential and usually exceeds a carrier's fleet capacity. To overcome this problem Song and Regan (2003) suggest to restrict the number of routes selected to be equal to or less than that carrier's fleet size. Also they also note that in practice, large trucking companies regularly contract for more routes than they can serve and sub-contract excess demand as needed. But in our model in constraint (18), we apply capacity restrictions and this capacity may take into consideration overbooking of capacity. We do this because our objective function is maximizing revenue and thus avoids the possibility of tours, which might have high empty costs but might bring in more profits.

6.4.2 Tactical NR Model

In this section we present an operational model taking into account the strategic/tactical issue of system balance. In this formulation we model the system level flow balance constraint:

$$\begin{aligned} & \text{Max} \quad \sum_{j=1}^J p_j f_j y_j \\ & \text{s.t.} \end{aligned}$$

$$\sum_{j=1}^J a_{ij} y_j \geq u_i \quad \forall i \in I \quad (20)$$

$$\sum_{j=1}^J y_j \leq W \quad (21)$$

$$\sum_{j=1}^J q_j y_j \leq q \quad (22)$$

$$y_j \in Z^+ \quad (23)$$

where q_j - flow imbalance each tour in $j \in J$

Constraint (22) models the system level balance while generating tours. Each tour consists of a set of nodes which have a flow imbalance i.e. flow into the node is not equal to the flow out of the node based on shippers forecasted demands or the carriers pre-existing demands. The term q_j represents the total flow imbalance on all the nodes in the tour.

6.5 VOLUME BASED CONTRACTS

In strategic bidding, the important thing is to achieve system balance i.e. minimizing empty repositioning and improve asset utilization. The focus is on which lanes, zones and points in the network to consider and how these geographic markets will impact expected revenues over the length of the contract. In this section we develop operational rules to procure the packages with a consideration of three carrier divisions (small, medium and large) in mind. The main procurement problem for TL carriers can be formulated as a

transportation problem for a very simple case. We also provide a formulation for strategic bidding in auctions for volume-based contracts. The carrier is assumed to have pre-existing commitments and is bidding strategically in an auction to stabilize the excess and deficits units at each node in the network. Also volume contracts do not focus on developing closed loop tours, which reflect an expectation of real time execution of a continuous tour.

From a strategic point of view we ignore some operational details pertaining to fleet management: i) vehicle dispatching, ii) scheduling of crews and iii) maintenance operations. Typical fleet management optimization models only refer to allocation of vehicles to customer requests and repositioning of empty vehicles. Vehicles need to be moved empty to bring them certain places to satisfy the forecasted demand, which is realized at some future time. Though this is not a profitable move it helps *empty balancing*, i.e. the distribution of empty vehicles to balance supply and demand in future demand periods is a major objective of dispatchers and a central component of fleet management.

Fleet management is generally treated as an operational problem. The whole purpose of a contract bidding in CA is to remove the inequities in geographic demand and supply. In this we take a long-term view of the problem and define a transportation procurement problem, which we call the **Strategic Transportation Procurement Problem (STPP)**.

The carrier has a set of depots (for domicile purposes), and each vehicle is assumed to return to the depot after the completion of the transportation service. Let $G(V, A)$ be the

network. The carriers have information of the demand for loads from V_{ij} where $i, j \in V, i \neq j$. The carrier bids in the auction process to try to balance the flow in the network with a constraint on the amount of volume of lanes she can bid on the network. STTP is defined as follows:

STTP

$$\min \sum_{i \in V'} \sum_{j \in V'} c_{ij} x_{ij}$$

s.t.

$$\sum_{j \in V'} x_{ij} \leq S_i, i \in V \quad (24)$$

$$\sum_{i \in V'} x_{ij} \geq D_j, j \in V \quad (25)$$

$$x_{ij} \leq V_{ij}, \quad \forall (i, j) \in A \quad (26)$$

$$x_{ij} \in Z^+ \quad \forall i, j \in V \quad (27)$$

where:

c_{ij} - the operating cost from i to j

S_i - surplus capacity (or deficit loads) originating from Node i

D_j - deficit capacity (or surplus loads) originating from Node j

x_{ij} - volume transferred from i to j

V_{ij} - shipper truckload demand from i to j

For feasibility of the SSTP, the following condition has to be satisfied:

$$\sum_{i \in V'} S_i \geq \sum_{j \in V'} D_j \quad (6.28)$$

Constraint (6.28) says that the total capacity must be greater than total demand or pre-existing commitments. Based on their experience, carriers know that some of their contracted loads will not materialize and hence they actually overbook their capacities, similar to airline overbooking. In the case the in which a carrier cannot satisfy a shipper's demand, the carrier will sub-contract the loads to a different carrier possibly at a higher spot market rate. The variables S_i are in fact inflated capacities.

Proposition 6.2: Using the STTP model is an optimal way for carriers to bid on single lane volumes for achieving system balance.

Consider the case $V_{ij} \gg D_j, S_i \forall (i, j) \in A$, then constraint set (26) can be relaxed and the STTP problem becomes the classical transportation problem. The carrier does not have enough capacity and pre-existing demands to satisfy all the demand of the shipper. The solution from STTP, provides a solution for minimizing empty reposition and taking into account pre-existing commitments. The other exogenous and endogenous factors can be taken into account using the appropriately chosen cost function. As can be seen from the formulation, the solution generates the volumes to bid on each lane. These volumes can be used to develop operational tours on which to bid. This will help the carriers to obtain network balance and to improve their bidding process. This same process can also be applied directly to the simpler single lane bidding problem to achieve system balance. The bids from this formulation can be used to generate closed loop tours, conditional bids. This problem can also be used as a basis for hedging against supply and demand uncertainty by treating the V_{ij} as random variables. Capacity uncertainty can also be

included by treating the variables S_i and D_j as random variables. Another important thing about the formulation is it is easy to solve even if the formulation is integral.

6.5.1 Package Definitions

In this section based on the STTP we develop a scheme to generate OD packages. OD packages can be defined as packages, which predominantly i) start at an origin and end up at several destinations ii) start at different origins and end up at one single destination.

Some preliminary definitions:

Surplus Node: Each node, which has excess fleet capacity positioned for performing transportation service and a deficit of loads. A node i is surplus node if $S_i \geq 0$.

Deficit Node: Each node, which has excess demand but a lack of capacity to provide transportation service. A node j is surplus node if $D_j \geq 0$.

Lane: A lane is an origin destination pair. A lane can also consist of several links. For the purpose of notation we will use l for lane and $l = i \rightarrow j$, where i is the origin denoted by $O(l)$ and j is the destination node denoted by $D(l)$. V_k is defined as the number of truckloads to bid on lane l_k , where k is the lane index.

Volume Package: In an atomic bid with volumes, the package consists of lanes and their lane volumes along with the bid prices. Mathematically a volume atomic bid with a bidding price p is defined as the following $[\{(l_1, V_1), (l_2, V_2), \dots, (l_N, V_N)\}, p]$. A disparate

package is a volume bid with no apparent relationship between the origins and destinations of the lanes in the package.

Round Trip: Round trips begin and end at the same node i . The destination of one lane is the origin of the next lane in the package. For a package with lanes $\{l_1, l_2, \dots, l_N\}$ the following relationship exists: $O(l_1) = i, D(l_1) = O(l_2), \dots, D(l_N) = i$. In this package the carrier wants to advantage take of economies of scope by constructing a round trip.

Origin Package: In an origin package, lanes emanate from a single node i . Mathematically we can define it as $[\{(l_1, V_1), (l_2, V_2), \dots, (l_N, V_N)\}, p]$ $\forall l, O(l) = i$. The package consists lanes with one single origin to different destinations. This implies that the origin has an excess capacity at that node.

Destination Package: A destination package consists of lanes with a single destination and different origin nodes. In a destination package, lanes congregate at a single node j , which has excess loads or deficit capacity. Mathematically we can define the package as $[\{(l_1, V_1), (l_2, V_2), \dots, (l_N, V_N)\}, p]$, $\forall l, D(l) = j$.

Based on the surplus and deficit nodes we can create packages to achieve system balance. A carrier first scans through all the nodes in the network and can easily determine the excesses and deficits of capacity. The carrier runs the STTP model and determines the volumes of lanes to bid to obtain balance in the network. For each surplus node, an origin package can be developed depending the link volumes that emanate from the node in the STTP solution. Likewise, can create a destination package for each deficit node

depending on the volumes entering this node. Using this we will get the OD packages. We can also develop a more formal analysis of developing packages using insights from the dual of the SSTP.

6.6 SIMULATION METHODOLOGY

In this section, we use an optimization-based simulation methodology to understand the impacts of various factors in carrier bidding. We consider a Euclidean shipper network with denoted by $G^S(V, A)$ and carrier's network denoted by $G^C(V, A)$. The shipper provides the lane-demand structure to participating carriers. The formulations presented in section 6.6 (both NR models) serve as the basis for the bidding policies used here. For finding potential routes, the route generation scheme defined in section 6.4.1 is employed. For networks of even moderate size, the number of tours generated by a depth first search is huge. The simulation assumes weekly demands and that the tours generated are completed within a week. The tours are constrained by length and time and they include domiciling constraints. Even though each tour is a closed loop, empty distances arise because of the domiciling constraints. For example if a carrier starts from point A to B and from B to C where AB , BC are shipper lane demands, the carrier has to return to point A and this will generate an empty movement CA . Our main objective though is to select tours where these empty distances are low and also to select higher revenue generating tours. Simulation scenarios were run thirty times for different densities of loads. The objective of the simulation is to understand the impacts of various exogenous and endogenous variables. Rather than develop a solution methodology for

the NR models we use the CPLEX solver directly.

Standard pricing scheme: (operational and strategic factors)

$$p = c_j \times (1 + \beta - \gamma_j + \delta_j) + e_j \times \alpha_j \quad (34)$$

Where c_j is the total cost of serving the new lane(s) in that atomic bid; e_j is the empty cost associated with not securing re-loads; β is the carrier's average profit margin (strategic component), α_j is the carrier's risk of not tendering any future demand on those empty lanes j , γ_j is the package discount factor and, δ_j is the incumbency consideration of the carriers (strategic). Since normally a carrier's cost is proportional to distance, we use distance to represent cost. Other factors may also be added into the pricing schemes. These include individual carrier discounts and risk factors. We will discuss the assumed parameters in the next section.

In our simulation we assume that naïve or small carriers mostly use single lane bids. This is in keeping with the belief that large carriers' have greater technical sophistication and serve a greater portion of shipper's network and hence bid more packages (Plummer, 2003). Carriers are assumed to be small (naïve bidders) or large (advanced bidders) carriers, which use the ONR and TNR models. Carriers developing packages offer carrier (multi-lane) discounts because of improved vehicle utilization and reduced deadhead miles and dwell times. In our simulation we assume that package discount parameters are drawn uniformly from five to fifteen percent of the overall lane costs in the package. For some packages or lanes, the carrier is an incumbent and understands the shipper's

business, so the carriers give an incumbency discount between $[-2\%, 2\%]$ to take into account the credibility of the shipper's operations. Profit margins are generated for each carrier, which are uniformly distributed between $[profitMin, profitMax]$ for each carrier and package dependent. In this industry minimum profit margins are generally around 5% and the maximum profit margins are generally within 25%.

If the tours contain single lanes, the carrier does not need to take into account the probabilities of a re-load. But in a continuous tour we assume that the probabilities of tendering a load is given by a Poisson distribution, so the dwell times can be modeled using an exponential distribution, for simplicity. This information is carrier specific or the shipper might help to estimate these values based on the historical load tendering. Though our formulations consist of ex-ante probabilities, it is difficult in practice to actually have the necessary data for every bid. Again the probabilities can be reflected using the pricing scheme.

Models developed to date do not explicitly consider the effect of demand uncertainty. In practice, bidding should depend on temporal, spatial and seasonal variations. In fact, there are many things to consider. Even if we consider only temporal variation of demands, the simplest assumption would be a uniform temporal distribution of loads. Or, taking the worst-case scenario, the carriers could assume the demands to be presented during a single peak season. Carriers usually give volume discounts. Volume discount bids allow the carriers to specify the price they charge for a lane as a function of loads that will take place in the future. Bids take the form of supply curves, which specify the price that is charged per unit of load when the loads tendered lies within a particular

interval. We assume that the shipper takes into consideration the demand uncertainty using the strategic pricing factors.

To understand the performance of our bidding strategies we will use the following metrics: expected profits earned by each carrier in the bidding process, the number of lanes won by each carrier (business volumes), shipper costs and also the average percentage of lanes not allocated using the allocation process. In the simulations we include a dummy carrier so that the set- partitioning formulation will be guaranteed to be feasible. The incumbent costs and lane costs for the dummy bidder are set very high. The percentage of lanes allocated the dummy bidder indicates that these lanes are not profitable for the carrier's business. In the simulation, ex ante we perform bidding and then run the auction and calculate the above metrics to understand the ex post impacts.

6.6.1 Effect of different bidding strategies

In this section we test the three bidding strategies Naïve, ONR and TNR. The simulations are performed for thirty runs for each lane density on a randomly generated Euclidean network. As shown in Figure 6.1 the ONR strategy wins around 90% of the total profit. In these simulations the shippers fails to allocate 10% of lanes when the two carriers are Naïve and Advanced.

Naive vs. Advanced carrier

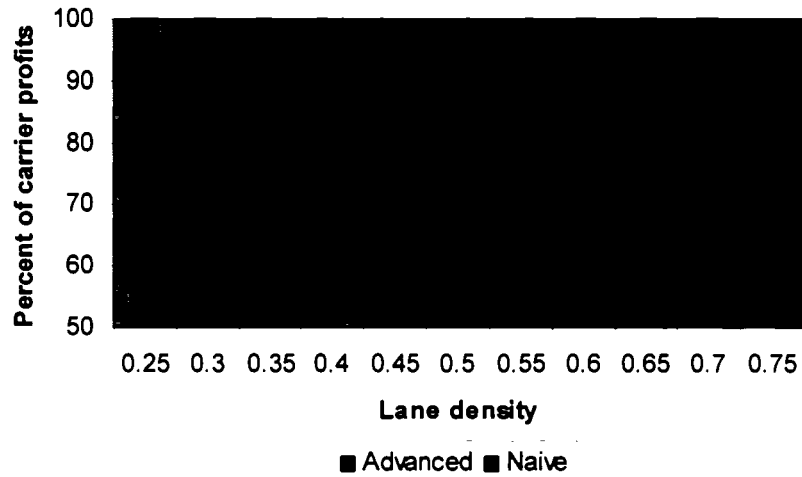


Figure 6.1 Simple vs. ONR Carrier

From Figure 6.2 we can see that the ONR model performs better on the average than other models. The carrier who considers system balance wins a high percentage of lanes at lower lane densities, but the proportion of lanes awarded to him decreases as the lane density increases. This is because as the lane density increases system imbalance is proportionally increased thus the lanes become less attractive to the carrier.

From our simulation using the three kinds of bidding strategies we see that around 12% of the shipper's lanes are not allocated to the carriers. This is due to carriers not bidding in any lanes as small carriers are constrained by fleet size and the large carriers with optimization bidding strategies do not find these lanes profitable.

Naive vs. Advanced Strategies

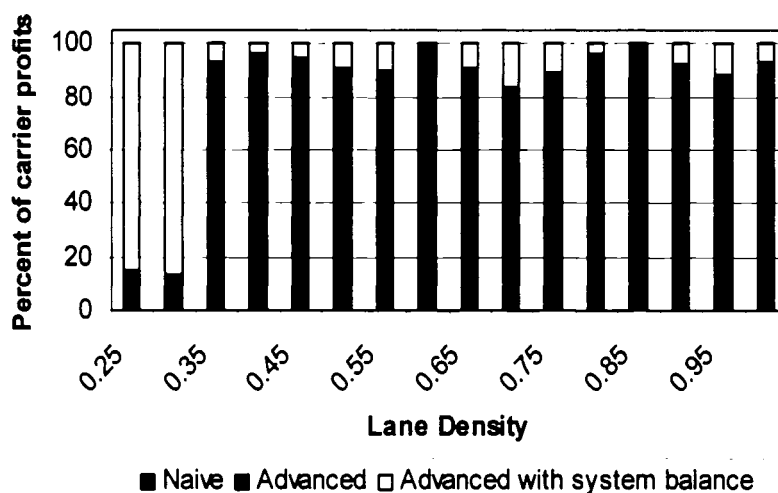


Figure 6.2 Naive, Advanced, System Balance Carrier

6.6.2 Effect of shipper's business rules

In this section we look at the effect of shipper's business constraints on the bidding process. According to Plummer (2003), carriers believe that most of the time package bids do not win in the auctions due to shipper business rules (side constraints). The carrier bidding in CA involves a lot of computational strain to make packages and they may still not be awarded these packages. Using simulations for the three bidding strategies, we will try to understand how the following side constraints; incumbency and maximum-minimum carriers and coverage, affect the bidding process. The winner determination problem is changed to accommodate these side constraints in bidding for the auctions. We will also assume that the carriers do not know which side constraints are considered by the shipper.

Since we have only three kinds of bidding strategies for incumbency we will assume one carrier is the incumbent and the rest are new carriers. The new incumbency penalties are fixed one-third of the average profits obtained from the simulations in the section 6.6.1. If the naïve bidder is the incumbent, then we find that even with different lane densities of new loads the advanced carrier always wins. Including incumbency costs the percentage of lanes not allocated rises to 12% on the average (an increase of 2% without the incumbency considerations). The shipping costs for the shipper increase by 5%. Likewise if the naïve shipper is the incumbent and competing with the carrier with system balance consideration, the naïve carrier wins 40% of the profits, but the total allocation of lanes to this carrier is poor around 45%.

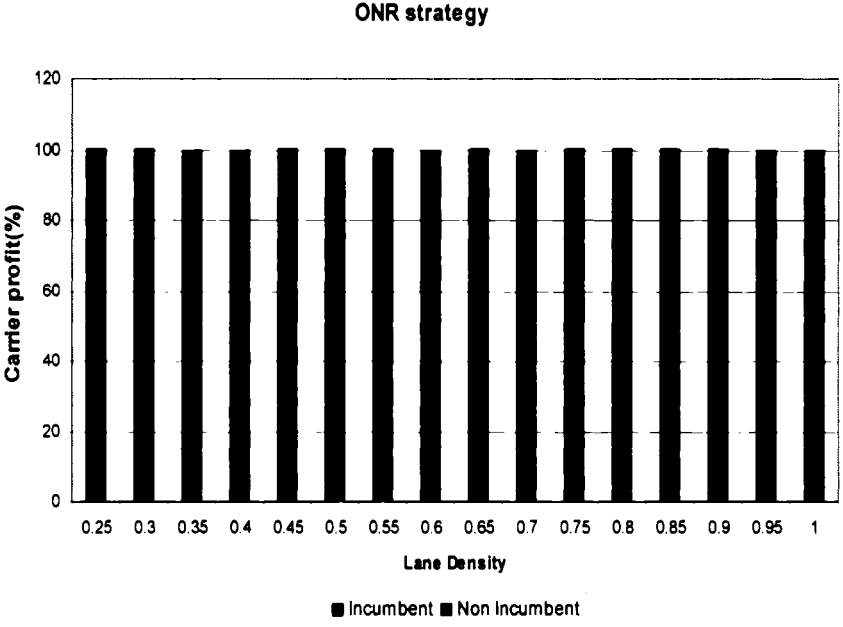


Figure 6.3 Incumbent ONR vs. Non-incumbent with ONR strategy

If incumbency is considered between two carriers with the ONR model, the incumbent carrier performs better, as expected. The incumbent carrier performs 40% better than the non-incumbent. Also with these two strategies the percent of loads not allocated is just 4% (about 10% for naïve vs. advanced carriers with ONR).

If incumbency is considered between two carriers with the TNR model as shown in Figure 6.4, the incumbent carrier on performs marginally performs better than the non-incumbent carrier.

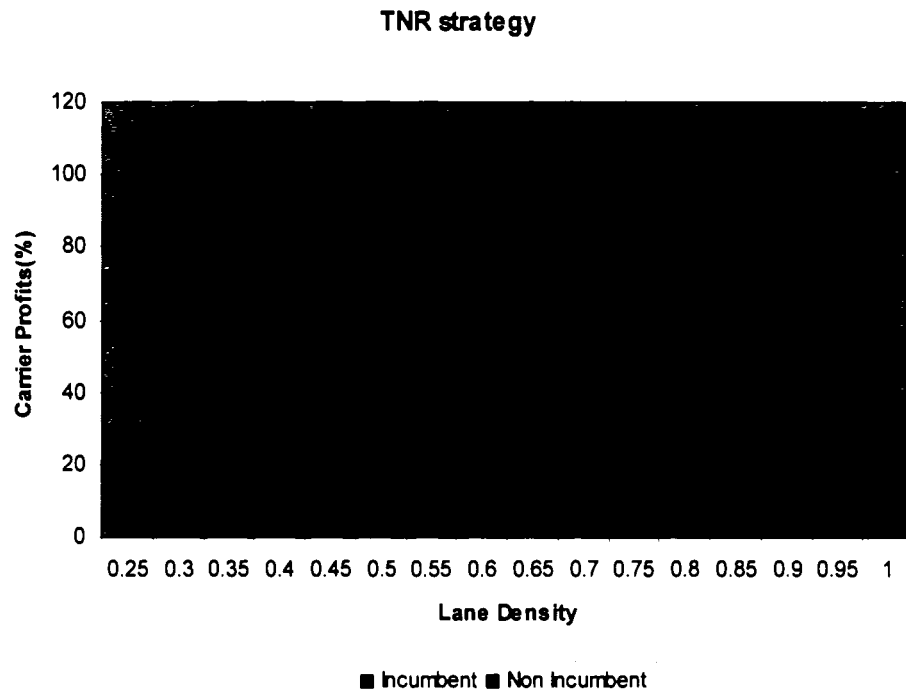


Figure 6.4 Incumbent vs. Non-incumbent with TNR strategy

For the coverage constraints with two ONR carriers, the constrained carrier wins on an average 70% of the profits.

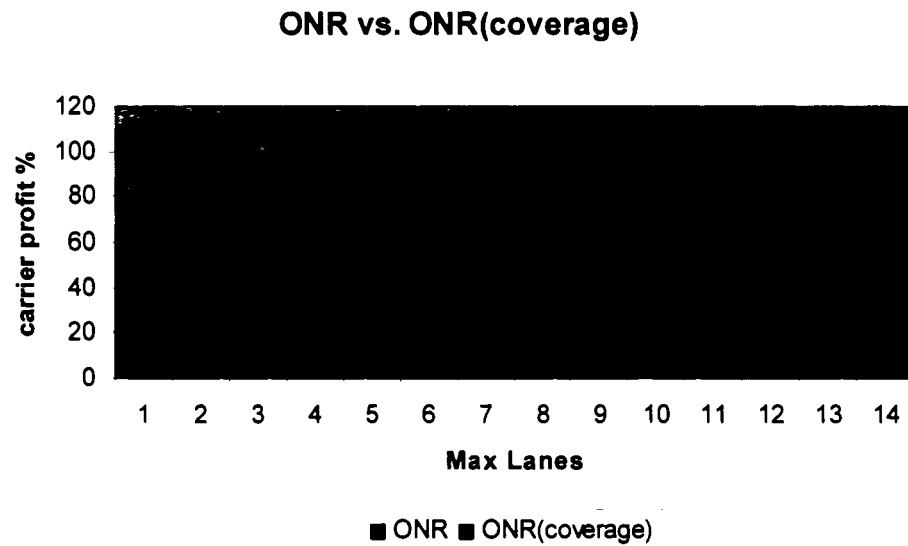


Figure 6.5 ONR vs. ONR(coverage)

The ONR strategy as a whole performs better with the coverage constraints than the Naïve bidder or the TNR strategy.

6.6.3 Effect of Node Potentials

For simplistic purposes we consider a network, where the US freight transportation network is divided into six regions (Plummer, 2003). Ledyard et. al. (2002) also consider this type of scenario but divide the US into eight regions. We follow the

assumptions on values of node potentials used by Plummer (2003). The author presents a regression equation about the dependence of carrier cost on the regional factors or node potentials with the different regions as the independent variables. In our study we use their regression coefficients as node potential to understand, based on these costs, how the carriers actually fare in the bid process. We assign node potentials for these six regions and use the individual lane-pricing scheme described in section 6.3.2 to take these node potentials into consideration.

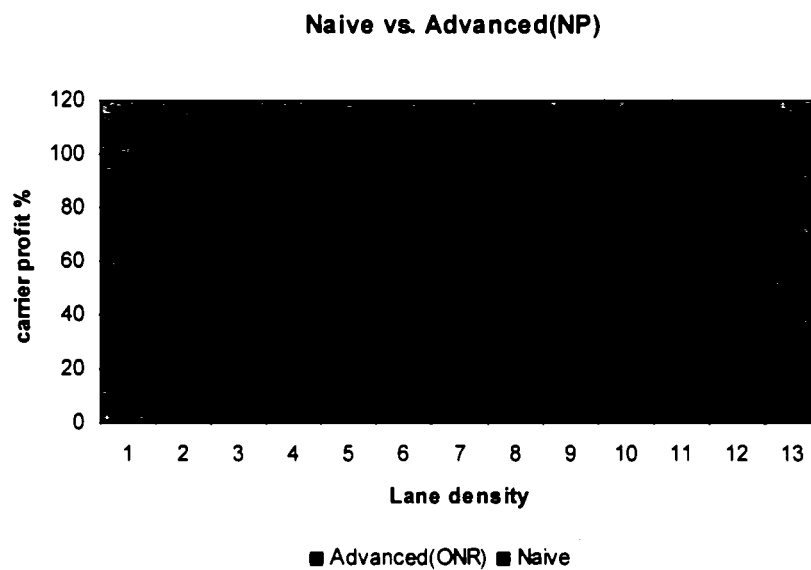


Figure 6.6 Naïve vs. ONR strategy with node potentials

Using node potentials shows that the ONR strategy on average generates more profits than the Naïve strategy from Figure 6.6 and similar to the profit percentage in 6.6.1 where simple strategic price bidding generates a profit percentage close to 90% and using node potential pricing the profits are about the same. However, the important thing to note is that shipper costs increase and the number of lanes allocated decreases to 17%

with the coverage constraints while it was 10% without the coverage constraints.

ONR vs ONR(NP)

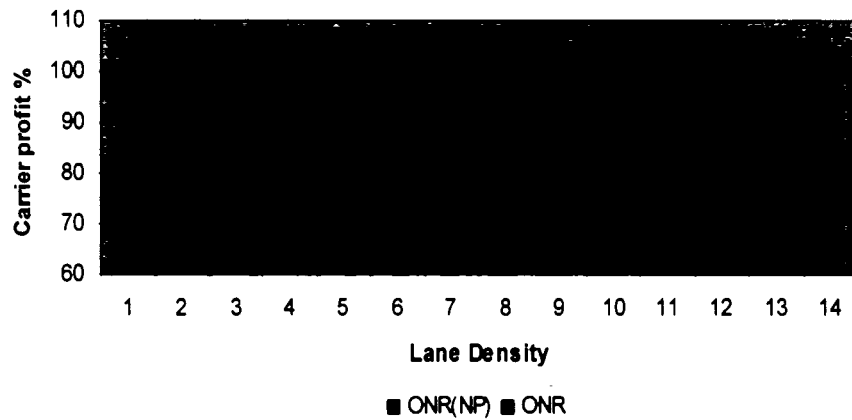


Figure 6.7 ONR vs. ONR strategy with node potentials

ONR vs. TNR(NP)

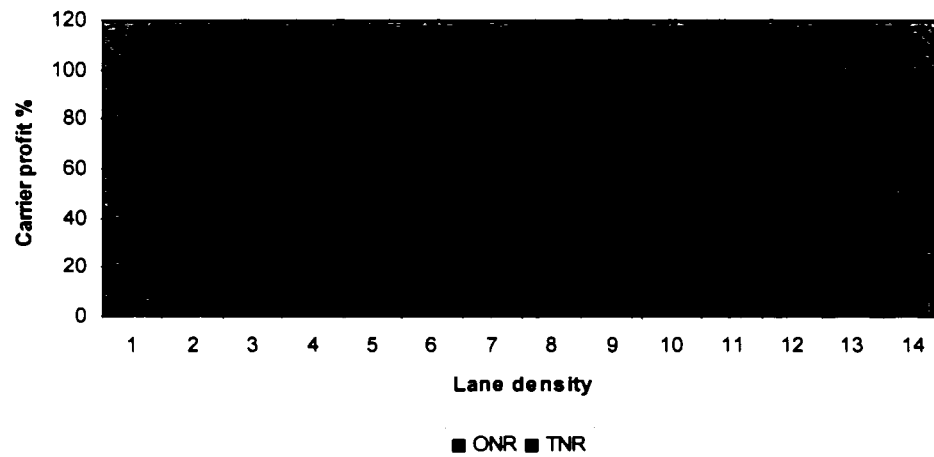


Figure 6.8 ONR vs. TNR strategy with node potentials

The ONR strategy has an unbeatable advantage over the ONR strategy with strategic pricing as the profits generated are around 95%. This clearly shows that advanced carriers should taken into account the effect of node potentials while evaluation and pricing of

bundles. TNR bidding with node potentials performs marginally better when competing against the ONR strategy, the TNR carrier profits increase by 5% and the business share of loads also increase.

Summary of simulation results:

- ❑ The ONR model performs better than Naïve or TNR model. TNR model performs well at low load densities in-terms of total ex post profits, but this bidding might induce system imbalance to the carrier. Bidding using the TNR model on the average generates less profit.
- ❑ The carrier considering system balance performs poorly in general when compared to the ONR strategy, but we can believe that the loads offered by the shipper does not provide balance to the carriers operations. System balance also implies cost minimizing by cutting down empty repositioning.
- ❑ Incumbency considerations are not affected for the ONR model when competing with a Naïve carrier. An incumbent carrier with ONR strategy also does really well against a non-incumbent ONR carrier.
- ❑ Maximum minimum coverage constraints favor the ONR strategy from our simulations. The ONR strategy is very good for a carrier without pre-existing commitments as a whole.
- ❑ Node potentials really impact carrier bidding. ONR strategy with node potentials pricing almost wins all the business lanes in the bidding process against a carrier with ONR with strategic pricing or TNR carrier.

6.7 BIDDING IN UNIT AUCTIONS

In unit auctions, the shipper clearly specifies what packages we are going to

bid on and wants a dedicated move for these sets of packages. The carrier has to just look at how this network will pan out in the future based on the demand profile. In this stage the carrier can just use a common values assumption to bid on these packages. The problem though simplifies because of the fixed number of tours to consider. This can be modeled using the NR models described above.

CHAPTER 7 SHIPPER COLLABORATION

In this era of heightened competition many companies have turned to supply chain partners to collaborate to decrease their inefficiencies in operations and cut costs. Collaborative Transportation management (CTM) appears to be the wave of the future for the logistics industry. Supply chain relationships are changing from adversarial to collaborative ventures.

In this chapter we study the problem facing an intermediary, a third party logistics company or an online auction market of achieving collaboration for transportation demands from a group of customers. The problem is tackled from a strategic and tactical perspective, which gives rise to different formulations. We formulate the problem as a set-covering problem and examine the cooperative issues facing the coalitions in the problem from a game theory perspective.

7.1 INTRODUCTION

The current buzzword in the logistics industry is collaborative transportation management (Browning and White, 2000). CTM is defined as the collaboration between the shipper and the carrier to forecast transportation shipments and ensure their accurate fulfillment (Esper, Williams, 2003). The logistics industry is currently facing extreme pressures due to exogenous factors such as increasing fuel costs and high driver turnover. Driver turnover ratio in the truckload industry is about 103% (ATA, 2004). The industry also

suffers from poor planning which can lead to empty backhauls, which can be avoided by making the empty haul to a competitor or other shipper. To remove this inefficiency, the shipper can negotiate a better route if they provide continuous collaborative moves, which reduce asset repositioning and empty movements. The focus of this chapter is to facilitate shipper collaboration, studying it from the perspective of N -person cooperative game theory. The chapter tries to shed light on how game theory can be used to solve the shipper collaboration problem.

Methods in practice include Shipper-to-Carrier collaboration and Shipper-to-Shipper collaboration. The most popular is Shipper-to-Carrier collaboration. This collaboration provides better visibility and communications between these business partners by conducting their contract management, freight execution and tracking through a web-hosted network. Nistevo is one example of this kind of collaborative network. International Paper is one company taking advantage of this type of collaboration by using the transportation management software from Nistevo, another is Land O'Lakes which is estimated to save seven to ten percent of their costs of moving over 19,000 annual shipments through the Nistevo Network (Nistevo.com).

The next type of collaboration is Shipper-to-Shipper collaboration. This collaboration teams two or more shippers that combine their routes to reduce deadhead and convert one-way freight to dedicated freight (a more economical alternative). Examples of this in practice include Georgia-Pacific who has over 575 tours/shared routes within its internal divisions and with other shippers like General Mills. They have reduced their deadhead to 3.2% on average from about 12% deadheading before, and are experiencing

a 5-7% savings on freight. The 575 tours are over a year with some frequency (Nistevo.com).

The problem we examine is as follows: The intermediary (3PL or online anonymous impartial auctioneer) has a set of shipper O-D demands to be satisfied with carrier fleet. The demands are truckloads from each origin to destination. The objective is to find routes to minimize the backhaul costs by utilizing the empty trips. In the next stage these routes are put on an auction for market clearing. The fleet may be homogeneous or heterogeneous but for the sake of simplicity we try to just consider the homogeneous case. Many 3PL companies face this problem and some online freight marketplaces explicitly tackle this problem (Nistevo.com, Transcore.com). Shipper collaboration has been first studied in literature by Savelbergh, Ergun, Kuyzu (2003). Song and Regan (2004) consider the case of an auction marketplace run by a coalition of carriers who collaborate with each other and share the costs among them.

7.2 LITERATURE REVIEW

Savelsbergh, Ergun, and Kuyzu (2003) first studied shipper collaboration in the literature. The authors try to find continuous tours, which can be repeated with certain frequency from a strategic perspective and on shipments being full truckload. The problem is to find minimum set of weighted cycles in a network such that all the lanes are covered. They consider unit demands only. They formulate the Lane Covering Problem (LCP) as a minimum cost flow problem (polynomially solvable). They also extend it to the cardinality-constrained lane covering problem where the number of arcs (stops) are constrained. Length constrained LCP finds the minimum cycles constrained by length.

A dual fitting greedy algorithm is presented. A factor-revealing algorithm is also presented.

They discuss data structures to solve this problem also present the underlying complexity of generating huge cycles. The problem of infeasible cycles becomes more pronounced when time windows are considered and the carrier might have to wait at some point. This waiting time should also be reduced. After this analysis, the authors turn to determine if there exists a stable allocation of the shippers. The payment to the carrier must be such that it is equal to his cost and also determine how much each shipper has to pay the carrier. Other factor is collaboration that it is Pareto optimal, no shipper would be better off by not collaborating. The problem is hard in the sense that gain sharing mechanisms are hard to find. They try to develop algorithms for approximate cost recovery and stability.

The use of co-operative game theory for cost allocation in freight distribution problems has been studied before. The papers by Engvell (1996) look into the cost allocation problem faced by Nordisk Hydro, Sweden. The paper develops a vehicle routing game (VRG) to facilitate a study of how to allocate the costs. Dynamic alliance auctions (Ihde, 2004): In this problem the author presents an auction mechanism for freight auctions with shipper alliances. The authors study the impact of different payoff methods for the package tours formed in spot markets.

7.3 METHODOLOGY

We look into shipper-shipper collaboration problem to improve asset utilization and

reduce logistic costs. According to Elogex, the definition for collaborative logistics “which results in shared efficiencies and cost savings throughout the supply chain and across the supply chains of newly-formed trading partners.”

Shippers have demands for transportation and the carriers the capacity to move them. These two entities converge at a neutral electronic marketplace(ex: Nistevo, TransCore) and the neutral arbitrator tries to find routes for shipper to collaborate. Without loss of generality, we can assume that shippers present a set of unit demands. The ‘demand’ is moving a truckload from an origin to a destination, which we call a ‘lane’ in transportation environment. The main aim is to find continuous moves or collaborative continuous moves by merging the collaborating shipper’s networks together to remove transportation inefficiencies.

The time horizon for the collaborative tours is typically a week in practice to prevent driver turnover ratio. Some of other tour restrictions are the maximum lanes on a tour, maximum length, time window feasibility, deadheading, empty haul movements and domiciling constraints. The problem is to find suitable set of collection of items such that shippers collaborate and the number of vehicles used is minimized. Here we are only interested in finding the collaborative routes and make no assumption how these will be assigned to the carrier. This is a reasonable assumption because the neutral market place (NMP) usually a 3PL, has contractual agreements with carriers and our purpose in this paper is to look at the market clearing mechanism using shipper collaboration. Another assumption is that the collections of these demands must be more than one because then only we can say that some sort of collaboration is taking place.

A transportation network can be represented as a complete graph $G = (V, E)$ with n nodes and non-negative edge weights c_{ij} where V – set of nodes, E set of arcs connecting the vertices. The graph is strongly connected and follows triangle inequality implies we restrict ourselves to only Euclidean graphs. For simplicity the following things are assumed in the model. The carriers have depots at different vertices and the vehicles have to come back to the same depot (domiciling constraint). The operational considerations that are assumed in the model are vehicles come back to the depot (single or multi-depot), assumptions about initial repositioning and unit demand per lane.

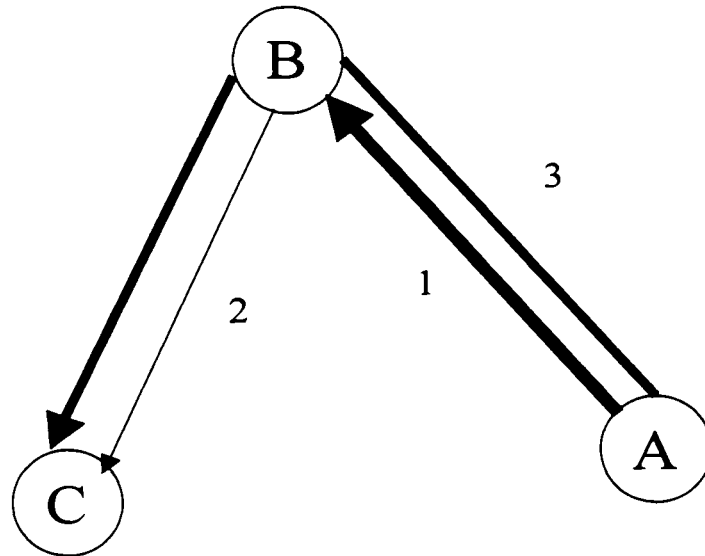


Figure 7.1 Shipper Collaboration

To provide an example for mixing of lanes from different shipper as shown in Figure 7.1 is a network with two links AB and BC. We have individual demands for lanes AB from Shipper 1 and for lane BC from shipper 2. If we use two different trucks each truck has to make an empty movement. But instead a collaborative move: $ABC = \{1,2\}$ can be

made utilizing one truck and thus saving empty backhaul costs. Route 3 is the collaborative move. Every collaborative move has two costs: cost without collaboration and cost with collaboration

$f(AB)$ - Cost of satisfying the demand for lane AB

Cost without collaboration: $W_1^{NC} = f(AB) + f(BA) + f(BC) + f(CB)$

Cost with collaboration: $W_1^C = f(AB) + f(BC) + f(CA)$

Profit from the collaborative move: $P(1) = W_1^{NC} - W_1^C$

As defined above, we can generate tours taking into consideration domiciling constraints of the carriers, node potentials, time windows of service, duty hour restrictions and length of the tour. In a typical truckload problem a tour consists of multiple of truckload pick-up and deliveries for a one-week period.

Our objective is to maximize the profits. A decision variable is chosen for each collaborative move.

Notation:

$I = \{1, 2, 3, 4, \dots, N\}$: set of lanes in cross shipper network

i : index of a lane in set I ;

j : index of a tour in set J which includes multiple lanes;

p_j : profit of collaborative tour j ;

a_{ij} : shipper's cost to select carrier k to serve tour j ;

We also have the decision variable:

x_j : equal to 1 if tour j is selected as a continuous move;

We call this problem, *shipper-shipper collaboration problem (SCCP)*. The analogy here is simple, each bid package refers to a collaborative move. In a package we have a set of lanes that we bid on. In this problem there are no singleton bids i.e. a package containing only one lane. The formulation for the problem is:

$$\begin{aligned} & \max \sum_j p_j x_j \\ & \text{s.t.} \\ & \sum_j a_{ij} x_j \leq 1, \quad \forall i \in I \end{aligned} \tag{1}$$

$$x_j \in (0,1) \quad \forall j \in J \tag{2}$$

The problem is a set-packing problem, which is NP-hard. For an extensive literature of the set packing problem the readers are referred to Balas and Padberg (1976). Theoretically collaborative tours that can be formed at worst case are exponential.

De Vries and Vohra (2003) present important applications and review of state of the art solution methodologies for the set packing problem applied to the combinatorial auction applications. The formulation is similar to the combinatorial auction formulation with the restriction that packages (tours) are complementary and do not consider substitutable packages. Each package or tour has an embedded min-cost path over the links. In a simple graph with a set of links, the minimum cost path to traverse all the links exactly once and end at the same vertex is called an Euler's circuit. In a standard vehicle routing problem (VRP) a set of demands at a node have to be satisfied. In this problem the demand is a movement from a node to another node. Hence in a sense there is a

demand for lanes. So we are more interested in covering these lanes in a minimum cost fashion. This means we have to solve a Directed Chinese postman problem (DCPP), which belongs to the class of polynomial complexity and can be solved by using a minimum cost flow formulation. For an extensive literature on arc routing problems the reader is referred to Dror (2000). Hence the cost of a directed cycle with traversing over the lanes in a package exactly once can be done in a polynomial time.

The tours generated are continuous tours and because of domiciling constraints only a single carrier will be awarded the tour in the final contract. In the case a carrier wins two tours that start and end from the same depot then we can combine these tours if the tour restrictions are met.

Proposition 7.1: Tours generated from the SCCP problem contain mutually exclusive sets of lanes.

The proposition follows from the constraint set (7.1) as each lane is included in only one tour. This observation will be used to generate a stable payoff mechanism.

Proposition 7.2: For shippers and carriers, combining two feasible tours provides a complementary tour.

For a single – depot case p_j is always non-negative. Hence the cost functions are sub-additive. Let M be the index of the single depot.

Let $j_1 = \{M, V_1, V_2, \dots, V_A, M\}$ and $j_2 = \{M, U_1, U_2, \dots, U_B, M\}$

$$p_{j_1} = f(MV_1) + f(V_1, \dots, V_A) + f(V_A M)$$

$$p_{j_2} = f(MU_1) + f(U_1, \dots, U_B) + f(U_B M)$$

$$p_{j_1 \cup j_2} = f(MV_1) + f(V_1, \dots, V_A) + f(V_A U_1) + f(U_1, \dots, U_B) + f(U_B M)$$

$$p_{j_1} + p_{j_2} - p_{j_1 \cup j_2} = f(MU_1) + f(V_A M) - f(V_A U_1) \geq 0$$

$p_{j_1} + p_{j_2} \geq p_{j_1 \cup j_2}$ because of triangle inequality.

7.3.1 Linear Relaxation

What happens when the decision variables are continuous? Each lane has certain volume characteristics. All the volumes on the lanes must be totally satisfied.

$$\max \sum_j p_j V_j$$

s.t.

$$\sum_j a_{ij} V_j \leq 1, \quad \forall i \in I \quad (3)$$

$$0 \leq V_j \leq 1 \quad \forall j \in J \quad (4)$$

Solving this problem given an optimal solution of the vector x and the profits generated p . In the linear relaxation V_j is the percentage of the total volume of each lane in route j that used for a periodic routing. This problem is better to solve because it gives the 3PL alternative portfolios to form collaborative tours. The carriers always have to

deal with shipper demand uncertainty and this approach helps the best fit as time goes along. This model is slightly different from Savelsbergh, Ergun and Kuyzu (2003) lane covering problem. A 'lane covering problem' finds the set of directed cycles that cover all the lanes.

The 3PL still faces a difficult problem of finding the right collaborative tours. Further, the 3PL has to make these decisions over all the shipper demands, which might be a huge task. To find efficient solution procedures and to decrease the problem of generating solutions all at once, an iterative algorithm in the line of iterative combinatorial auction mechanisms would be helpful (Parkes, 1999). The other important research direction is to analyze the dual problem and see the individual value of the lane components. The problem is to find the set of collaborative moves that will be stable is still a daunting task. In the next section, we provide some heuristics for Pareto efficient payment sharing among the shipper's after the tour has been put in the auction to be bid by carriers.

7.3 SHIPPER ALLIANCE FORMATION

In this the problem we define, these collaborative moves are set out to bid in an auction. The problem now becomes of how much each shipper to pay the carrier winning the collaborative move. Based on the SCCP problem we can set a reservation price. The SCCP problem can also be used to solve the development of packages for the shippers in unit auctions described in Chapter 4. Generally a most stable allocation will be computationally intractable as the tours are formed from the solution to the SCCP problem and it might not be computationally feasible to consider all the tours to begin with. Shippers are self-interested; hence need a stable payoff division mechanism,

if not shippers will not join the consortium and that is the main thrust of the problem.

Another way of looking at the problem is to take into consideration the perspective of cooperative game theory. A cooperative game (I, C) consists of $|I|$ players with a characteristic (cost) function $C : \Xi \rightarrow R_+$ where Ξ , the set of feasible collaborative tours. From proposition (7.2) we know that the C function is sub-additive.

Basic theoretical question is to find:

- *Simple coalition schemes that are in the core of the game.*
- *Payoffs based on the costs and execution of each lane in the tour.*

Without loss of generality, consider a tour generated from the SCCP problem indexed by $I = \{1, 2, \dots, N\}$, the set of lanes in the tour and the reservation price for this package is p_I (costs with collaboration). From now on each lane and shipper will be used interchangeably as we assume in this tour each lane is a different shipper demand. Let $y = \{y_1, y_2, \dots, y_n\}$ be the *imputation* vector if and only if $\sum_{i \in I} y_i = C(I)$. y_i can be interpreted as the amount assigned to each lane i . For the imputation y to be in the core, if and only if $y(S) = C(S), \forall$ subsets $S \subseteq N$, where $y(S) = \sum_{i \in S} y_i$. A *core* of the cooperative game is a solution concept that is fair and also stable i.e. no shipper would be better off by not co-operating with the other shippers in the tour.

Payoff scheme 1: Each lane is assigned to pay the carrier proportional to the length of the lane.

For a shipper collaboration of N lanes the vector of distances for each lane is (l_1, l_2, \dots, l_n) for the carrier and in the final auction a carrier was awarded this tour for a final bid price B . Using payoff scheme 1, each lane $i \in I$ pays the winning carrier a price equal

$$\text{to } \frac{bl_i}{\sum_{j \in I} l_j}.$$

Proposition 7.3: Payoff scheme 1 is in the core of the system.

The carrier bid price has to be less than the reservation price, according to the definition of the reservation price. From this we get the following relationship:

$$b \leq p_i \tag{5}$$

The payoff division ratios are given by the vector: $\left(\frac{l_1}{\sum_{i \in I} l_i}, \frac{l_2}{\sum_{i \in I} l_i}, \dots, \frac{l_n}{\sum_{i \in I} l_i} \right)$ (6)

The shippers have to pay a vector of costs: $\left(\frac{l_1 b}{\sum_{i \in N} l_i}, \frac{l_2 b}{\sum_{i \in N} l_i}, \dots, \frac{l_n b}{\sum_{i \in N} l_i} \right)$ (7)

Equation (7.8) defines the imputation vector. The system payoff is $y(I) = b$. Intuitively

this is the amount that the shippers in the tour I are required to pay the winning carrier.

$$y_j = \frac{bl_j}{\sum_{i \in N} l_i} \quad (8)$$

$$\sum_{i \in S} y_i = \frac{b \sum_{i \in S} l_i}{\sum_{i \in I} l_i} \leq \frac{\sum_{i \in S} l_i}{\sum_{i \in I} l_i} p_I, \forall S \subseteq I \quad (9)$$

The question here is if the shippers are better off by forming a tour S instead of being in the tour formed by I . If this were the case we would get a tour S from the solution of the SCCP, as can be seen from the formulation the subsets of lanes in final solution would be mutually exclusive (proposition 7.1). From proposition (7.2), we know that the costs are sub-additive and a feasible super tour I is more beneficial to the shippers and the carriers.

The term $p_I \left(\frac{\sum_{i \in S} l_i}{\sum_{i \in I} l_i} \right)$ can be interpreted as the allocation of cost for the tour S from the

SCCP formulation. Hence each subset of shippers in the tour will benefit from being in the tour I also clearly. The derivation is clearly straightforward and the payoff mechanism is in the core of the system. The payoff scheme may not be the optimum division as generally in the SCCP problem as it is impossible to generate all the possible feasible tours even for medium sized networks, but it is still in the core of the current set of generated tours. Also shippers can gain an additional advantage from the carriers in the auction depending on the bid price as can be seen clearly from Equation (5).

In the generation of the tour there might exist empty lanes in the tour $(l_1, l_2, \dots, l_n, e_1, e_2, \dots, e_m)$. We propose two payoff schemes to tackle empty lanes:

- a) Divide empty lanes proportionally among the shippers.
- b) Divide empty lanes based on the contribution to each load lane.

Payoff scheme 2: Each lane (or shipper) is assigned to pay the carrier proportional to the length of the lane and the empty distances.

For a shipper collaboration of N lanes and M empty lanes, the vector of distances for each lane is $(l_1, l_2, \dots, l_n, e_1, e_2, \dots, e_m)$ for the carrier and in the final auction a carrier was awarded this tour for a final bid price b . Using payoff scheme 1, each lane $i \in I$ pays the

winning carrier a price equal to $b \left(\frac{l_i + \sum_{j \in M} e_j / |I|}{\sum_{j \in I} l_j + \sum_{j \in M} e_j} \right)$.

Proposition 7.4: Payoff scheme 2 is in the core of the system.

In this case we assign a lane length equals $\sum_{j \in M} e_j / |I|$ to each shipper and from payoff scheme 1, each shipper has to pay an allocation with the ratio

$\frac{l_i + \sum_{j \in M} e_j / |I|}{\sum_{j \in I} l_j + \sum_{j \in M} e_j}$, which is in the core.

Payoff scheme 3: Each lane (or shipper) is assigned to pay the carrier proportional

to the length of the lane and the contribution of empty distances by each lane.

For a shipper collaboration of N lanes and N contributions of the loaded lanes to the empty lane distances, the vector of distances for each lane is $(l_1, l_2, \dots, l_N, e_1, e_2, \dots, e_N)$ for the carrier and in the final auction a carrier was awarded this tour for a final bid price B . Using payoff scheme 1, each lane $i \in I$ pays the winning carrier a price equal to $b(l_i + e_i) / \sum_{j \in I} (l_j + e_j)$. Further more the empty distance contributions can also be considered as the penalties for each shipper on a lane for failing to conduct shipment execution properly thereby causing a disruptive influence to the overall tour execution.

Proposition 7.5: Payoff scheme 3 is in the core of the system.

The payoff follows from core payoff scheme 1, and each shipper has to pay with the

allocation ratio $\frac{(l_i + e_i)}{\sum_{j \in I} (l_j + e_j)}$.

CHAPTER 8 CONCLUSIONS, SUMMARY AND FUTURE

RESEARCH

This dissertation addresses the main issues surrounding auctions for truckload service contract procurement. Truckload procurement auctions exhibit inherent interdependencies among bidding items and hence auction mechanism designs should take these into consideration. The auctions and bidding depends on the market structure. Two primary markets exist in truckload procurement i) spot markets and ii) long-term markets. For spot market transportation procurement, the use of classic auctions is predominant, but the literature on carrier bidding in these auctions is minimal. For long term markets combinatorial auctions are used but these tend to be computationally complex for both the bidders and the auctioneers. Though there exists a large body of literature on how to design a combinatorial auction, the auction design for transportation auctions is limited and much of the existing research is not directly transferable. In this research we propose the use of an auction scheme with shipper-defined packages to reduce carrier-bidding complexity. Lagrangian algorithm development is performed to help shippers solve the winner determination problems with non-price business side constraints. Bidding in combinatorial auctions is an intractable problem as it includes solving difficult optimization problems with the added complexity of competitive behavior and decision making in a stochastic and dynamic environment.

Transportation auctions exhibit asymmetries and incomplete information and identifying stable bidding strategies is exceptionally difficult. Bidding strategies in spot markets for carriers are examined and a sensitivity analysis of the different parameters for carrier bidding in long-term combinatorial auctions is presented. To achieve shipper collaboration and facilitate cross shipper auctions, we propose a shipper alliance formation using mathematical formulations and identify payoff schemes for shipper cooperation.

In the following, the first section provides a synopsis of previous chapters and summarizes the contributions of this research; the second section discusses extensions and future research directions.

8.1 RESEARCH SYNOPSIS

This section in brief summarizes the contents of this thesis. We first provide the necessary auction background and examine their applicability for freight procurement.

8.1.1 Transportation Auctions

In freight procurement auctions the shipper is the auctioneer and the carrier is the bidder. Shippers have to decide the format and rules of the auction, the information given to the carriers and the non-price business constraints to include in the winner determination problems. The shipper has to deal with stochasticity arising out of the uncertainties in demand, network performance and carrier operations. The shippers need auction mechanisms that are incentive compatible and ideally produce solutions, which are robust to future disruptions. In this dissertation we first classify auctions as spot and long-

term auctions as the auction mechanisms design and carrier bidding are different. We point out these differences and suggest suitable auction mechanisms for market clearing.

Combinatorial auctions seem to be the preferred auction methodology in practice and literature. The development of optimal means for solving winner determination problems and for bidding is also important. For combinatorial auctions of lanes, both the winner determination problem (WDP) and the carrier's bidding problem are NP hard problems. Though small scale WDP's are solvable, many assumptions are made. The biggest of these is that the demands offered by the shippers are correct when in fact these can be highly stochastic. Similarly, the carriers assume that they can safely predict their future capacity is also an unreasonable assumption. In the future, means to incorporate stochasticity in the offering, bidding and winner selection processes should be developed. These problems offer rich opportunities for researchers. In some cases the shipper must resort to using approximation algorithms to solve the WDP and ensuring fair allocations in such cases is very important. The carriers face significant computation strain in bid evaluation in combinatorial auctions. Due to this we examine other viable auction mechanisms.

8.1.2 Electronic Spot Markets

B2B e-Commerce is rapidly growing and has led to the development of online marketplaces for freight transportation service contract procurement. We present the present landscape of existing electronic marketplaces and look into the operational auction models in use. Because of their simplicity classic auctions like first price, second

price English and Dutch auctions are being used. In freight exchanges, double auctions are the chief auction mechanism.

The method of conducting procurement electronically departs significantly from traditional procurement and hence full-scale acceptance will take time. The growth of the Internet led to the development of a huge number of electronic marketplaces in the late 90's, but these had difficulties delivering significant value. However, the present trend of consolidation and forming strategic alliances with other logistical companies will help to provide tangible values to the shippers and the carriers. These marketplaces are more prevalent in Europe because of the proximity of the neighboring countries and shorter distances. In the US where the hauling distances are typically very large, the use of spot markets introduces uncertainty in the market. Carriers typically like to have guaranteed contracts as the cost of driving back empty cuts into profits. Though the general consensus is that Internet and e-commerce will provide value to the supply chain, carriers are also hesitant because they think the sites will cut margins and also not give them a chance to explain the differentiated services they provide. Shippers' on their part are hesitant to enter the online marketplace for short-term cost savings because they fear that service quality will be impacted.

The success of the online marketplaces depends on whether they can attract the critical mass for desired transaction efficiency and provide value added services to improve logistical processes. At present many markets are in a stage of consolidation and a few strong online transportation markets will emerge.

The carrier's problem in spot markets is very difficult. Carrier fleet management is

itself complex and bidding in online marketplaces adds to this complexity. The dynamics involved in bidding strategies, negotiation and utilizing the information in bidding environments must be better understood to develop methodologies to aid the carriers. In carrier bidding problems, the decision to bid on the combinations of lanes to serve and the price to charge is a strategic decision. Carrier profits depend on the price parameters and fleet management.

The selection of the loads to bid depends the fleet management characteristics for the current and future time horizon. The evaluation process also has to take into consideration the kind of service in question (truck load, LTL etc.). The carriers are also involved multi-lateral negotiations or multiple spot auctions or procuring contracts using traditional means for the same transportation capacity. From a carrier's perspective, the yield management problem in electronic marketplaces involves choosing the electronic auctions in which to participate, setting the bid prices depending on the auction format. In multi-round auctions, the questions of interest include the minimum bid increments and the bid stopping rules.

We present a literature survey of market clearing mechanisms models for online freight transportation marketplaces. Current research into the strategic behavior of shippers and carriers conducting their business in these market places is lacking. Models for shipper-carrier strategic interaction are presented for freight transportation procurement using the private value and common value economic auction models. We also present an analysis of when these models can be applied and develop insights into symmetric bidding in classic auctions.

8.1.3 Unit Auctions

Auctions are currently the dominant price discovery mechanism for large shippers seeking to procure transportation service contracts with logistics companies. The bid analysis problem is of critical importance to shippers and determines which contracts are assigned to which carriers and at what price. In practice this problem is further complicated by the consideration of a shipper's business rules, such as restrictions on the number of winning carriers, constraints on the number of packages won and the preferences for incumbents or other known carriers. In Chapter 4 we examine a version of auction mechanism problem in which the packages put out to bid are mutually exclusive. The shipper, who has a better understanding of lane demand structure than do carriers, develops packages of lanes and asks dedicated carriers to bid for the right to serve the packages. Bundling of lanes also satisfies the "economies of scope property", an important consideration in long-term auctions. This is known as a unit auction and may be preferable to full combinatorial auction both to shippers and carriers under certain circumstances. The carriers' problem of bid evaluation in combinatorial auctions is difficult and bidding on packages with synergies leads to less computational strain on the part of the carriers. An extensive analysis of unit auctions is presented and mathematical programming models for winner determination in these auctions are formulated. Greedy heuristics and Lagrangian relaxation based heuristics are developed to solve the models. Numerical results show that our Lagrangian relaxation based heuristic performs better than other heuristics and that the solutions are very close to optimal. The lagrangian heuristics perform much faster than CPLEX for very large test instances and provide

solutions very close to optimal.

8.1.4 Non Price Business Constraints and Lagrangian Heuristics

In Chapter 2 we present the non-price business constraints faced by the shipper solving winner determination problems in long-term auctions. In Chapter 4 and Chapter 5 we model and develop heuristics for winner determination problems with side constraints. While this work represents an effort to model and solve the sophisticated bid analysis problems in transportation procurement auctions, several topics need to be examined and elaborated in the future. First, while this work modeled the most common business considerations explicitly, these rules may vary in practice from shipper to shipper. In addition, shippers may prefer to conduct sensitivity analysis to determine which business constraints should be included in the model.

In Chapter 4 we present a solution methodology to solve shipper winner determination problem in the presence of shippers' business side constraints, namely incumbent costs and minimum-maximum number of winning carriers. Mathematical programming formulations are provided for bid analysis that incorporate these side constraints in a single sourcing and multiple sourcing unit auction mechanisms. A Lagrangian heuristic methodology is outlined to solve these bid analysis problems and empirical analysis on test problems, are presented. The Lagrangian heuristic's performance was tested over 100 randomly generated test instances and is also very competitive computationally compared to CPLEX. In case of very large test instances usually encountered in transportation

procurement, the heuristic was able to generate solutions efficiently with duality gaps within 6%, outperforming CPLEX.

In this chapter 5, we consider the bid analysis problem faced by shippers with sophisticated business constraints in combinatorial auctions for the procurement of transportation services. This chapter examines this problem by formulating the shipper's business rules as side constraints in an integer-programming model. In freight procurement for combinatorial auctions the best formulation is a set partitioning formulations. However, in supply chain procurement auctions set covering formulations are predominant because of the property of free disposal.

We look at different model formulations and test the applicability of lagrangian heuristics in Chapter 5. First we develop a set covering formulation for the winner determination problem with incumbency constraints. The Lagrangian results show very good duality gaps within 1% and most of the cases we find the optimal solution from the Lagrangian heuristic. However CPLEX solution times are faster than our Lagrangian heuristic. Next we develop formulation for winner determination problems with minimum-maximum side constraints for a multiple and single sourcing scenarios. Empirical results show that the duality gap between upper and lower bound in the lagrangian relaxation heuristic is 10% to 20% for winner determination problems with minimum-maximum carrier constraints. CPLEX also generates optimal solutions faster than our Lagrangian heuristic. Finally we consider a model with incumbency, minimum-maximum and coverage constraints and test a Lagrangian heuristic. Set partitioning formulations with side constraints are very difficult to solve. The results for test instances show a maximum

gap of 20%. In our Lagrangian heuristics, the upper bound generates solutions very close (within 10%) to the optimal solution we obtain from CPLEX. The upper bounds also are generated within first ten to twenty iterations of the Lagrangian iterative process. This fact and the polynomial complexity of lagrangian duals makes the heuristics very attractable to be embedded in a branch and bound framework for generating optimal solutions. Overall our results suggest that a set covering formulations for combinatorial auctions can provide better duality gaps than the set partitioning formulations.

8.1.5 Bidding in Long-term Auctions

In Chapter 6, we study the carrier-bidding problem in long-term auctions. First we review the existing literature of bidding models for freight transportation procurement in combinatorial auctions and point out the important factors for the consideration of bidding in truckload markets, for example, cost interdependencies, information structures, system balance, etc. We classify bidding into categories: unit contracts and volume based contracts, for the sake of simplicity and develop tractable models for bidding. The chapter presents unit contract formulations for the carrier from a revenue maximization and system balance point of view. The problem facing the carriers is compounded because of the exogenous and endogenous and factors. For example, the uncertainty in winning the bids and the variety of information structures, the uncertainty of demand and supply and the competitive nature of auctions and shipper business constraints. As bidding in combinatorial auctions is a heuristic process, we resort to an optimization based simulation analysis to study the effectiveness of our bidding

strategies and impact of exogenous and endogenous factors in carrier bidding in unit contracts.

For volume based contracts a new formulation strategic transportation procurement problem is developed to estimate the volumes to bid on each lane. We argue that the solution strategy from this model is the best way to generate conditional bids for single lanes. Based on this model we provide insights to develop origin-destination package bids. The model is quite general and can also be used for bidding in spot markets.

8.1.6 Cross Shipper Auctions

Auction mechanisms are being used increasingly for transportation service procurement, especially by large shippers. In Chapter 7, we develop a framework to facilitate cross shipper auctions among small shippers. Nistevo, Elogex, etc. are examples of 3PLs which bring together small shippers to take advantage of their shipping networks to form collaborative tours. Collaborative tours reduce deadheading and dwell times for the carriers and shippers benefit by obtaining favorable rates. We formulate the shipper collaboration problem as a set-packing problem and tackle the cooperative issues facing the shipper alliances from a cooperative game theory perspective. Carriers bid on these collaborative tours and a stable payment scheme is necessary to determine how much each shipper in the alliance has to pay the winning carrier. In this chapter, we devise simple payoff mechanisms, which fall in the core (from a cooperative game theory perspective) of the collaboration problem.

8.2 RESEARCH CONTRIBUTION

The following are the contributions of this research:

1. We develop a framework for using auction theory models in transportation procurement and apply these models in spot markets.
2. We develop and examine unit auctions, which take into account the interdependencies of the shipper's network. In these the shipper rather than the carrier develops packages. We develop of Lagrangian relaxation heuristics to solve the NP-hard winner determination problems in these auctions. We also present formulations that include the shipper's non-price business constraints.
3. We develop formulations for combinatorial auctions incorporating shipper's non-price business constraints. We develop and analyze solution techniques for these formulations.
4. In bidding for long-term contracts we develop formulations for unit contracts taking into account system balance. We also develop volume contract formulations for strategic freight procurement.
5. We develop shipper collaboration models for use in facilitating cross shipper auctions. The uses of cooperative game theory for profit sharing are also discussed. Heuristics payoff schemes for shipper payments in cross shipper auctions are developed.

8.3 FUTURE RESEARCH

Transportation auction design and carrier bidding offers huge research opportunities. We briefly discuss some of the potential directions in this area of research.

8.3.1 Multi-round Auctions using Lagrangian Relaxation

The lagrangian heuristics presented in Chapter 4 and Chapter 5 can be used to handle multi-round auctions. The heuristics right now are presented for a single round auction case. Future research could be aimed at obtaining a better upper bound and lower bounds thereby reducing the duality gaps. Fine-tuning of the parameters in Lagrangian relaxation methods would improve the convergence of the sub-gradient optimization. Alternative approaches like the analytical cutting plane methods for solving the Lagrangian dual is another possibility. Another approach to tackle the problem is to develop a branch and bound algorithm, which uses the lagrangian solution as the lower bound at every node of the branch and bound tree.

A multiple round open auction can be facilitated using Lagrangian relaxation. In each iteration, the generation of feasible solution from the lagrangian dual optimal solution gives the information of current allocation of lanes to packages. Using this information, the carriers can be asked to bid on other packages, submit new bids or increase their bids on the existing packages. This will reduce the computational burden of carriers and also provide some information about the competitive nature of other carriers. Based on the Lagrangian information, an aggregate fixing scheme can be used to reduce the problem

size and finally a branch and bound algorithm can solve for the final allocation.

8.3.2 Auction Mechanisms for Carriers

In Chapter 3, we discuss an auction mechanism for carriers with capacity in which the carrier is the auctioneer. This auction scheme can be applied to LTL, rail, air and ocean carriers. Most of these capacity constrained service sectors use revenue management techniques, but little research has been done focusing on developing auction scheme for pricing issues. The linkages between yield management and auction theory is an interesting area of future research.

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