Iterative Combinatorial Auction for Carrier Collaboration in Logistic Services

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Abstract

In collaborative logistics, multiple carriers form a network to share their transportation capacities. Collaboration among carriers results in improved resource utilization and, therefore, reduced costs. In this thesis, we propose an auction-based model for carrier collaboration in transportation services. The model achieves carrier collaboration through facilitating the negotiation among carriers over a group of shipping orders required by one or a group of shippers. The negotiation is conducted through a combinatorial iterative auction mechanism with the objective of minimizing the carriers' overall costs.

We first present a centralized carrier collaboration problem model in which a central entity has all required information to compute an optimal solution. We then consider a more realistic game theoretic setting where auction-based mechanism is applied to deal with self-interests of carriers. Compared with one-shot auctions, the proposed iterative bidding framework has the properties of reducing carriers' information revelation and accommodating dynamic changes during the bidding process. Experimental results show that the procurement cost performance and the quality of solutions computed using the proposed iterative auction model is close to that of the optimal solutions.

Keywords

Logistics Carrier Collaboration, Iterative Descending Combinatorial Auction, Centralized and Decentralized Coordination, Multi-Agent Systems

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Introduction and Motivation

1.1 Background and Motivation

To maintain competitiveness in today's global economy, firms have to continuously improve the quality of their products and services and, at the same time, reduce their operation costs. A key strategy to achieve these objectives is outsourcing whereby a company engages an external partner to carry a portion of its operations. The most prominent advantage of outsourcing is cost saving by leveraging economics of scale realized in partner organizations, better quality, flexibility, and innovation. Outsourcing helps the organization to shift certain responsibilities to the outsourced company. In addition, outsourcing helps sharpening company's focus on core competences which results in improved quality of products or services.

Transportation service procurement is an important outsourcing activity in which a 3PL (Third Party Logistics) handle shipping of a company's products. Controlling costs and providing high service level make transportation service procurement an important task for companies. To answer the increasing demand for high service levels and customer satisfaction in today's volatile market, 3PL companies (carriers) have turned their attention to collaborative logistics, which can effectively improve resource utilization and reduce costs through collaboration between partner carriers. Collaborative logistics is focused on reducing costs which cannot be controlled or reduced by individual firms allowing all carriers pool their resources. Greater efficiency is achieved through sharing carriers' capacities to drop their empty backhauls cost and increase utilization rate of unoccupied capacities.

In this research, we study how to design collaboration mechanisms for carriers to coordinate with each other such that the overall cost of transportation services can be reduced.

1.2 Challenges

In transportation industry, shippers and carriers are under pressure to reduce their costs and operate more efficiently. In logistics collaboration, multiple shippers or carriers collaborate closely to form an alliance and consequently optimize their transportation operation through sharing vehicle capacities and/or delivery requests. Achieving the benefits of collaboration depends on close interaction between participants, identifying synergies and solving complicated optimization problems, which is challenging in a distributed market environment.

Classical collaboration approaches usually assume a centralized environment, in which a decision-maker has all the necessary information to compute an optimal solution. The centralized approaches are suitable for the settings where all carriers are belonging to a common holding entity or a single organization. However, real-world markets are essentially distributed. It is often the case that independent carriers need to collaborate in order to achieve better efficiency. These carriers are self-interested. They have private preferences and behave strategically to increase their own profits rather than the overall system performance. In addition to the computational complexities inherited from the large scale optimization in collaborative logistics, realizing the collaboration in decentralized environments presents additional challenges. First, the collaboration mechanism has to be designed to facilitate the interaction between independent carriers, such that high quality solutions can be realized through negotiation between carriers in an efficient way. Second, the mechanism has to be incentive compatible, that is, it can reach certain level of optimality despite the self-interested nature of carriers.

1.3 Approach and scope

To tackle the challenges of carrier collaboration in decentralized environments, we adopt market-based mechanisms, specifically an iterative auction model. Auctions have been applied to the design of a number of real-world markets. In past years, shippers procured transportation services for a set of bundles through obtaining multiple quotations from service providers, then the best offered price of a carrier or group of carriers were selected to perform the services. Recently, combinatorial auction (CA) approach has been designed to allow the carriers submit their bids for combination of distinct items. For example; a carrier company can bid for a round trip transportation services instead of bidding for an individual lane.

In this study, we provide a collaborative framework for carriers, which allows carriers select the profitable bundles of orders and final prices of the orders are determined by market competition at termination of the auction.

We proposed a combinatorial auction (CA) design for transportation service procurement which integrates the winner determination problem and carrier bundle optimization modeling. In particular, multi-round descending is used in which carriers as bidders solve optimization problems at each round to identify the highest profitable bundles of orders.

In terms of the scope, we focus on logistics services in centralized and decentralized frameworks. In centralized coordination, we assume carriers belong to a common entity and in decentralized coordination carriers are assumed as profit-driven agents. We also assume that an auctioneer coordinates the auction procedure. This auctioneer can represent a group of shippers who own the orders in the auction.

The aim of this study is to design a mechanism to distribute all proposed orders among the carriers with the minimum costs without revealing private information such as shipment costs of individual carriers.

1.4 Outline of the Thesis

The rest of thesis is structured as follows. Chapter 2 reviews previous studies on shippers and carriers collaboration in both centralized and decentralized environments with two transportation modes: TL (Truckload) and LTL (Less than Truckload). We also review various auction models and the auction-based carrier collaboration literature which is closely related to the work of this thesis. Chapter 3 presents detailed problem description in a centralized setting and cost assessment of a bundle of orders. Chapter 4 proposed an iterative auction model for carrier collaboration in decentralized environments. Chapter 5 describes system implementation and verifies the performance of the proposed approach through a computational study. Chapter 6 concludes the thesis and discusses future research directions.

Chapter 2

Literature Review

In logistics, multiple shippers and carriers can collaborate to optimize their transportation operation through sharing vehicle capacities and delivery requests. In this chapter we present background information of collaborative logistics, review the literature related to our work, and position our work in the picture of the literature. Since our objective is to develop an auction-based model for carrier collaboration, we also briefly review common auction models.

2.1 Collaborative Logistics

Collaborative logistics (CL) is a business model in which two or more companies form partnership. The main objective of CL is obtaining as much as possible efficiencies that equals to providing a better service with the same cost or the same service with a lower cost (Langley, 2000). CL environment allows all members pool their resources. Greater efficiency is achieved through sharing partners' capacities to drop their empty backhauls cost and increase utilization rate (Dai and Chen, 2009). It is understood that the partnership cannot be dominated by individual parties and have to be managed through a collaboration setting.

Partners can also be potential competitors. Collaboration among competitors demands a common platform to provide required communication and information sharing (Langley, 2000). Sutherland (2006) proposed several levels of collaboration. As shown in Figure 2.1, the volume of shared information increases at each level.

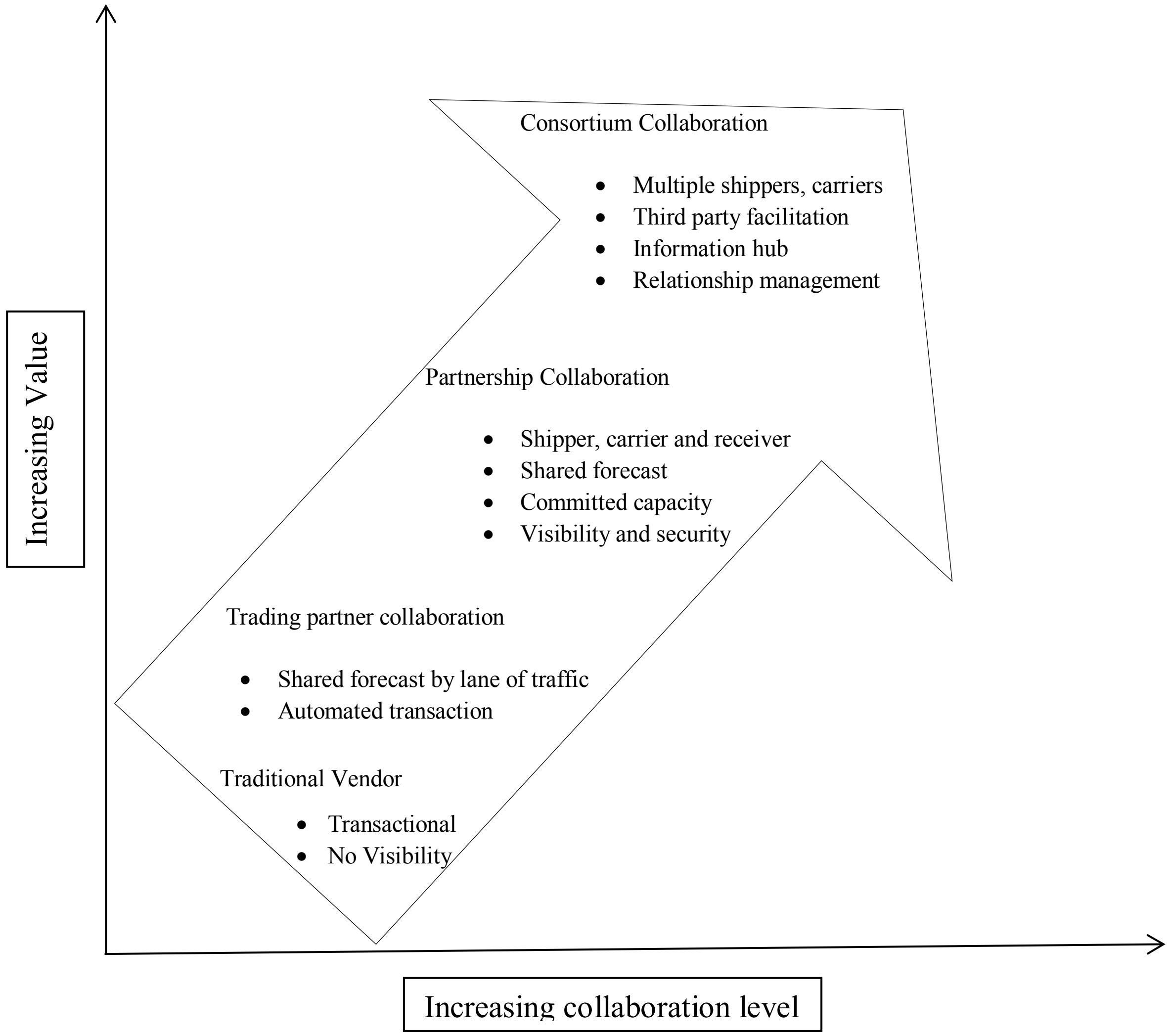

Figure 2.1: Increasing collaboration level versus increasing value (Sutherland, 2006)

There are multiple forms of collaboration ranging from strategic to tactical and operational levels. Strategic plans are mostly concerned with supply chain and asset planning, while tactical-level plans entails collaboration techniques and contracts. Operational collaboration is a highly dynamic form of collaboration which is to maximize asset utilization through a fleet routing management and scheduling. The main focus of our study is on carrier collaboration that is a type of collaboration at operational level.

Two types of road transportation are common in logistic services. TL (Truckload) transportation refers to movement of one type of merchandise with considerable volume from an origin point to a destination. In LTL (Less than Truckload) transportation, different types of goods with small quantities are shipped from multiple origins to different destinations. The advantage of TL (Truckload) transportation is that the loads never carry out on the routes while in LTL (Less than Truckload) mode the loads ship through multiple trailers. On the other hand, the advantage of LTL (Less than Truckload) is that the cost of shipment is much less when the load is only a portion of a trailer.

Based on the roles played in logistics, there are mainly two types of collaboration, namely shipper collaboration and carrier collaboration.In shipper collaboration, a group of shippers collaborate to aggregate their shipping requests and assign them to a single carrier. The objective is to find optimized path with the least empty backhaul. In carrier collaboration, multiple carriers collaborate in order to cut their costs through sharing their capacities in a set of lanes that pickup/delivery services will perform.

2.2 Collaboration through Centralized Coordination

Traditional CL research models assume centralized settings in which an optimizer or coordinator has all required information to compute optimal solutions and make decisions on behalf of the collaborators.

Agarwal and Ergun (2008) remarked that in a centralized setting, the profit/loss will be shared through a central planner with a fair mechanism. In a centralized environment, the optimal solution is chosen by a decision-maker and makes the system efficient. They mentioned that the main disadvantage for fully centralized system is being unrealistic in a practical situation. For example, carrier alliances with some carriers that operate with own assets, contracts, delivery schedule, costs and benefits will not follow a centralized setting.

In centralized approach, profit/loss sharing among players is very important, while in a decentralized system each player follows a strategy that maximizes his own profit and decisions based on local information.

Agarwal and Ergun (2008) also identified that a centralized system is applicable when a decision-maker selects an optimal solution for collaboration and shares the obtained benefits in a fair manner. However, in most of settings, designing a fully centralized system is not an easy task and a decentralized setting is recommended. In centralized systems an incentive mechanism has to be created to motivate individual partners to select a solution that results in maximizing the entire alliance.

There are several advantages and disadvantages for both centralized and decentralized systems. Centralized decision-making unites decisions and provides economies of scale. Moreover, centralization causes easy change in any process such as inventory policies or transportation sourcing. In a centralized system, the control of local businesses on crucial decisions is reduced due to the decisions that have to be taken centrally. In addition, all detailed information is not accessible for a central decision–maker to take optimal decision. However, in a decentralized setting, there is considerable misalignment between principal and agent.

It is obvious that centralization and decentralization can be effected by multiple functions. Competitive conditions and cost margins indicate the best decision for selecting the more profitable environment (Rangavittal, 2008)

Moore, Warmke, and Gorban (1991) implemented a sophisticated integer programming optimization model to obtain continuous movement in real time.

In traditional approach, operation research techniques are used to develop transportation schedule. A new challenge claims that traditional operation research is not efficient enough to address all problems and plans a suitable dynamic transportation network. Mes, Heijden, and Harten (2007) summarize inefficiency of operation research techniques through following four reasons: first, in order to implement optimization algorithms for a large number of operation research techniques, plenty of information is required. Second, global optimization methods are not compatible with updating information and may cause serious problems on the schedules. Third, in these sets of algorithms, unexpected failures or orders are not permitted to enter. Fourth, multiple independent organizations may have self-interested preferences and do not reveal the private information. Therefore, traditional approach like centralized setting is not capable to address all problems.

Mes et al. (2007) compare multi agent system to heuristic one on a hierarchical framework by considering vehicle distribution to nodes. They advocated agent systems performed considerably better than operation research in terms of service level, costs, and vehicle optimal utilization rate.

2.2.1 Centralized Approaches for Shipper Collaboration

Shipper collaboration focuses on a single-carrier and finds an optimal routing in a collaboration setting among multiple shippers. Through collaboration, shippers decrease or eliminate asset repositioning to a carrier to get a more favourable serving price.

Ergun, Kuyzu, and Savelsbergh (2007b) studied shipper collaboration in a centralized setting, formulated and solved Lane Covering Problem (LCP) in order to minimize truck repositioning in a Euclidean graph. They showed LCP is polynomialy solvable. Also, some other variants such as LCP with time windows, and availability of driver were considered in the model. They proved that all those variants were NP hard. Ergun et al. also proved that in computational experiment, better quality of solution would be obtained by generating more cycles. Briefly, for lane covering problem, a combinatorial optimization problem in shipper collaboration platform should be solved. Therefore, the assets repositioning cost would drop significantly.

Dai and Chen (2012) defined shipper collaboration as the collaboration among various shippers that all their requests would be provided by a carrier. By shipper collaboration, the optimal path with minimum empty travelling would be offered to the carrier. To achieve mentioned objective, shippers and carriers have to increase their profitability in order to survive in the logistics market competition. Asset repositioning is an applicable proposed solution.

Statistically speaking, in a total turnover transportation of $921 billion, the loss of empty truck movement is nearly 18% ,which is equal to a considerable value of $165 billion , and can be save potentially through an effective shipper collaboration. The aim of shipper collaboration is determining a set of lanes offering to a carrier as a bundle. Definitely, carriers prefer a bundle of lanes rather than the individual lane which will result in providing better quotation due to eliminating or decreasing repositioning costs.

This study has some strengths and weaknesses. For example, generating the cycles is a time consuming job, or there is no mechanism to share saved profit among the players while the proposed theorems with relevant proofs are significantly matured.

Ergun et al. (2007b) remarked similar vision to shipper collaboration, where a substantial portion of truck movements involves in empty truck backhaul. The study developed a model to identify repeatable and practical movements' tours employed frequently for TL (Truckload) shipments.

2.2.2 Centralized Approaches for Carrier Collaboration

Carrier collaboration considers how multiple carriers can cut their costs through sharing their capacities or orders in a set of lanes. Carrier collaboration study has been started and developed by several researchers in recent years. Carriers prefer the bundles of lanes that guarantee continuous movements. Term of "continuous moves" ideally equals to always having full truck with no asset repositioning cost.

Houghtalen, Ergun, and Sokol (2007) defined a group of carriers improved their profitability through collaboration. It is supposed that carriers may change a portion of their assigned loads in order to use their empty capacities in an alliance. However, the main objective of this collaboration is declining transportation cost through decreasing or eliminating empty return and exploiting optimal trucks' rate in the assigned network, which results in profit increment of the entire alliance.

Nadarajah and Bookbinder (2007) also proposed a carrier collaboration framework in LTL (Less than Truckload) setting. They consider loads exchange among carriers at the entry logistics platform of a city. In order to solve the collaboration problem, they applied three-phase heuristic methods. In the first phase, vehicle routing problem with time windows is solved by using an integrated tabu search that use constraint-programming engine. In the second phase, the facilities are located by using adaptive quadtree search model and in the third phase, a collaborative route is built. Moreover, they conducted computational tests and the results proved that a good collaborative cluster is a balanced mixture from different carriers. However, the model is not capable to address all problems in LTL (Less than Truckload) carrier collaboration.

Dai and Chen (2009) also developed a general mathematical model for logistics collaboration in LTL (Less than Truckload) setting with centralized mechanism. This model is suitable for both carrier and shipper collaboration. In this model, different shippers and/or carriers participate and form an alliance. The problem is formulated as a mixed integer programming with the objective of minimizing transportation cost of total alliance; lagrangian relaxation approach is proposed to solve the problem.

In carrier collaboration, collaboration will perform among multiple carriers in an alliance to handle transportation orders, and the result will substantially increase alliance profit (Dai & Chen, 2012).

2.3 Collaboration through Decentralized Coordination

Recently, decentralized system and distributed mechanisms have absorbed plenty of research interests. Agent-based system is a distributed approach with more flexibility and efficiency to a real dynamic world. In an agent-based system, each agent can be assigned for different objectives. Agent-based system has been applied for several important service domains. However, in this study, transportation service is the area of interest.

In transportation application, all agents are autonomous and are able to control their behavior against a common goal. In other words, in a decentralized system, it is assumed that all the players are selfish and they choose a strategy to increase their own profit. In multi-agent system (MAS), agents' behavior is autonomous by pursuing their own profit and interacts to each other in order to exchange information or using a negotiation mechanism. In a transportation alliance, each order (job) agent and each truck (resource) has its own goal. For instance, job agents insist in on-time delivery with minimizing possible cost, while resource agents focus on maximizing their profit and increase fleet optimal utilization rate. The main challenge is how to make close selfish agents' behaviors to optimal solution for whole system. Proposed solution can be a market mechanism like an auction (Mes et al. 2007).

Fischer, Müller, and Pischel (1995) pointed out that transportation planning and scheduling are inherently distributed and complex tasks. Geographically, trucks and jobs are distributed and also maintain some level of autonomy. To implement traditional methods, a scheduler must gather a large amount of information to a central place where the solution can be computed. However, using agent-based approach, an agent only requires local information. Lang, Moonen, Srour, and Zuidwijk (2008) also studied multi-agent systems (MAS) in logistics application. In this study decentralized is defined as moving away from centralized system which includes independency and flexibility. They defined that centralized setting was not able to address a complex and high degree of change and proposed the decentralized approach as an alternative suggestion . They conclude that planning problems in transportation have characteristics that comply with particular capabilities of agent systems. Specifically, these systems are able to deal with inter-organizational and even driven planning settings that meet supply chain's planning and requirements.

Auction mechanism, is a protocol that permits the agents to indicate their interests in one or more resources. Especially, combinatorial auctions (CA), have been adopted by a large number of shippers and 3PL (third party logistic) providers. Leading companies such as Wal-Mart, Procter & Gamble, and Sears have used combinatorial auctions to reduce their logistic costs (Sheffi, 2004)

Robu, Noot, La Poutré, and Schinjndel (2011) remarked that transportation and supply chain management is fruitful domain for application of agent-based electronic markets, particularly auction mechanism. This study is accounted as initial studies on an agent auction platform in a real business scenario in Vos Logistics Company with real orders and cost service providing. The pick-up loads are located in the south of Netherlands and have to be distributed across Germany. This study focuses on automating market interaction between different companies in a multi-party logistics negotiation and is able to integrate human bidders.

In decentralized coordination, Berger and Bierwirth (2009) studied a collaborating freight carriers alliance performing transportation services in a defined region. The paper focuses on exchanging transportation requests to facilitate collaboration among carriers. The framework's goal is maximizing total profit of the entire alliance. Three different strategies are examined in this study: a) carriers do not collaborate, b) carriers collaboration in a centralized setting, and c) carrier collaboration in a decentralized setting. They concluded that only in a win-win situation carriers share their private information. Therefore, a decentralized environment based on a confidential information sharing was proposed. Reassigning customer's requests was performed through two auctions mechanisms: vickrey auction (VA) or combinatorial auction (CA). The framework is able to determine the cost of decentralized approach against centralized setting and also absence of any collaboration framework. Although the cost of decentralization is considerable, there are the solutions such as widening the amount of centrally known information to relieve the cost. The results proved that more competition among carriers contributed to increment benefit of collaboration.

Ozener, Ergun, and Savelsbergh (2007) designed a simple lane exchange mechanism in a decentralized TL (Truckload) setting. Transportation costs breakdown in two main components: lane covering costs and repositioning costs. The main objective of proposed LP model is minimizing these two components in order to perform shipment requests through all the carriers of alliance in context of combinatorial transportation procurement auction. Proposed lane exchange mechanism is performed through four different carrier collaboration settings (mix sets of information sharing and side payment).Computational study shows that information sharing permits carriers to select their best strategy for choosing the possible lane exchange. On the other hand, side payment also is not an efficient approach.

Agarwal and Ergun (2008) also designed a platform to share profit of collaboration among the carriers in a decentralized multi commodity flow game. Linear Programming applied as a tool of model development. Through this mechanism, all players are forced towards collaborative optimal solution using inverse optimization method. This platform computes capacity exchange costs which allow a player receive the revenue from its demands or pay the other agents for using their capacities in a collaborative environment.

In the rest of this section, we will review multiple types of auction and analyze the auction proposed in transportation service procurement in a decentralized system.

2.4 Auctions

Theory of auctions is reputable as one of the most practical applications of system design in implementing a large number of real-world markets. In transportation services, it refers to a mechanism allocate lanes or shipping requests to carrier agents according to some regulations. Most of truckload transportation procurement research use auction-based methods and focus on allocating bundles of lanes to set of carriers with objective of minimizing total transportation costs.

Biswas (2004) defines the auction as a mechanism for allocating a set of goods to a set of bidders through biddings and asks system. In a classical auction, an auctioneer allocates an object to a bidder.

Auction is defined as a protocol which permits the agents express their interests in one or multiple resources and by using indication of interests determine allocation of payments and resources among them (Dai & Chen, 2012).

Kalagnanam and Parkes (2004) presented a framework for classifying auctions based on the requirements which are needed to set up an auction. Transportation auctions are categorized as following.

- <u>Resources</u> are the items that over them auction will be conducted. A mechanism includes a set of resources that can be a single or multiple items, and each item including single or multiple units (e.g. an origin-destination lane).
- <u>Market structure</u> is clarified by the nature of demand and supply .The auction is a negotiation mechanism that matches buyers and sellers.
- <u>Preference structure</u> determines utility of an agent for different outcomes. Preference structure helps the auctioneer to design the auctions in a way that the bidders with high values are allocated.
- <u>Bid structure</u>, in transportation, bids can be a single item, multiple units or bundle of items. For single item, bids need indicate the price and for multiple units, price and quantity have to be specified by the bids.
- <u>Matching supply to demand</u> also referred as winner determination problem or market clearing which is a mechanism to match supply to demand. The main issue is using single-sourcing or multiple-sourcing. In single-sourcing, multiple buyers and sellers compete whereas in multi-sourcing multiple buyers compete to a single seller or vice-versa.
- <u>Information feedback</u> is classified into two main groups: direct mechanism and indirect mechanism. In direct mechanism, agents will not receive any feedback

like price signal (e.g. sealed bid) while for indirect mechanism, provisional allocation or price signals provide useful information to the agents.

Generally, auctions have different players (auctioneer and bidders), the objects to bid on, participants' pay off function, and bidders' strategies. The object that bidders bid may be services, a single quantity or multiple quantities of objects. For better understanding of auction process, some of the functional expressions are defined as bellows.

<u>The equilibrium</u> is defined as the condition that any agent intends to change its bids and assumed as a best-response strategy to each partners. Multiple equilibrium types are introduced like: Nash, Bayesian Nash, and dominant strategy equilibrium.

<u>Efficiency</u>, based on a set of allocations, any agent can improve its allocation through making at least one agent worse off.

<u>Individual rationality</u>, defines that any bidder can be worse off after participating in an auction than before. In other words, the expected utility from participation in a mechanism is non-negative with a rational strategy.

<u>Incentive compatibility</u> indicates as bidder's best interests for bidding true valuations. Incentive compatibility is useful for auctioneers and bidders. The reason is that auctioneer will be informed how much is the agent's values over the items and it contributes to reducing complexity of the auction.

<u>Revenue maximization or cost minimization</u>, the auctioneer is the seller who desires to maximize its total revenue. In contrast, if buyer is an auctioneer, total costs should be minimized.

<u>Fairness</u> provides an allocation mechanism which is fair for all bidders in an equal opportunity to bid over the items. However, some players may feel unfairly treated because they are not selected as winner.

2.4.1 Auction Types and application domains

Various sorts of auctions are utilized in resource allocation mechanisms such as: single item auctions, Generalized Vickrey Auction (GVA), iterative bundle auctions, sequential and simultaneous auctions which have been studied extensively. We summarized some of these auction mechanisms as follows.

1- Single item auctions

This type of auction is useful for selling/buying a single unit of an item. Although it is used in the real market, in terms of computation approach is not important. English auction, Dutch auction and first (or second) price sealed-bid auctions are good examples of these traditional auctions.

2- Multi-unit auctions

Auctions involving the sale of different items are named multi-unit auction. Transportation domain can be a good example in multi-unit auctions area. In this auction, a buyer (shipper) and multiple sellers (carriers) wish to exploit economies of scale by using a volume discount auction. A lane with defined origin- destination, with a predicted demand volume in a specified time window can be an item for bidding.

3- Vickrey auction

Vickrey auction is an auction for multiple similar items. Bidders submit their demand simultaneously. Each bidder wins the demanded item at the clearing price, and pays the opportunity cost of its winnings. If there is only an item for bidding, the vickrey auction will be second-price auction. If the auction performs for non-identical item, the Vickrey auction referred to as generalized Vickery auction (GVA) or Vickery-Clarke-Groves (VCG).

4- Generalized Vickrey Auction (GVA)

GVA is single round second-price sealed–bid combinatorial auction, in which the highest bid will be the final winner, but pays the second highest bidding price. Therefore, a winning bidder can never affect the paid price. In addition, there is no incentive for any bidder to misrepresent its value. GVA is known as one of the most efficient auctions.

5- Iterative bundle auction

Iterative bundle auctions are indirect implementations of GVA. This type of auction is reputable for addressing computational and informational complexity of GVA. In this class of auction, the agents are allowed to reveal essential information as the auction progressed. However the exact and private information has to be kept uncover by the agents. This auction is designed for general combinatorial allocation (CA) problem.

6- Sequential and simultaneous auctions price bundles as the sum of each individual line, and assume that a set of preferred resources are auctioned in sequence. Agents bid on resources considering the past successes, failures, prices, and etc. The main application of this class of auction is in combinatorial or simultaneous items. Multiple goods sell in separate markets at the same time. The agents have to interact to separate markets in order to achieve a combinatorial of resources to accomplish their tasks

For years, combinatorial auctions (CA) and its applications applied in procurement methods and resource allocation mechanisms. In general, combinatorial auctions (CA) allow bidders to place bids on bundle of items. However, winner indication required solving hard valuation problems and winner determination (WD) problems which can be prohibitive. In general, combinatorial auctions cannot apply for likely large size problems. During a specific known sequence, bidders bid for their selected items. Past successes, failures and prices are effective indicators for bidding price to a distinctive bundle of items.

Biswas (2004) presented and compared some application fields of combinatorial auction (CA) summarized as following.

- Collaborative Planning

Suppose a set of jobs have to be executed by a system of robots at a lowest cost. In other words, *n* tasks have to be done by *m* robots, while each robot has a certain cost for performing the task. The overall aim is to allocate subsets of tasks to robots to minimize the overall cost.

- Electronic Procurement

Direct and indirect procurement can be performed through combinatorial auction. Suppose that a buyer intends to procure a bundle of items and sends RFQs to the several sellers. Buyer will receive the quotes and have to select the best bundles. Combinatorial auction (CA) is an applicable tool for selecting the bundles of mix bids rather than individual items.

- Job shop scheduling

In scheduling concept, a set of jobs has to be scheduled for a set of defined machines. Deadline and delay cost has to be considered for each job. The allocation of each individual job to the set of machines is another application of combinatorial auction (CA) problem.

- Supply Chain Coordination

Suppose a group of manufacturers needs some sort of parts that should be supplied through right combination of them. In addition, without supplying all types of components, manufacturer will able to run its production line. The problem is allocation of subsets of components to the manufacturer. Combinatorial auction (CA) is a practical approach to solve the problem and supply required products.

- Travel Packages

Selection of a travel package is another application of combinatorial auction (CA). Flights, hotel rooms, different entrainment tickets have to be allocated to the customers through such mechanism. Combination would be an important issue while a hotel room is useless without reserving a flight ticket.

- Course Registration

The main problem in course registration is allocating bundles of classes to the students. Each individual (student) has to be registered in some courses subject to meet minimum credits requirement and also any confliction among the classes is expected. Combinatorial auction (CA) mechanism can be a practical system for allocating classes to the students.

- Bandwidth Exchange

The bandwidth slots are exposed through public and private seller companies. There are also service providers who are called buyers and have valuations for bundles of bandwidth slots. Allocating combinations of bandwidth slots to buyers and adjusting them to sellers so as to maximize the total surplus in the system, needs a strong mechanism such as combinatorial auction (CA).

- Logistics Services

Logistics procurement or transportation service is one of the main applications of combinatorial auction (CA). Logistics services consist of shippers who assumed to be rational agents would like to ship bundle of orders from one or multiple origins to several destination nodes and carriers who sell transportation services and submit the cost of shipping orders.

Combinatorial auctions (CA) are classified in two groups; single-round auction and iterative auctions (multi-rounds). In a single-round auction, after solving winner determination (WD) problem, bidders are not allowed to submit new bids. Conversely, in multiple- round auction, the bidders are still permitted to submit new bids after solving winner determination (WD) problem.

In the next section, we will review some literatures focusing on multi-round auctions theory and mechanism design.

Iterative auctions include two different types: quantity setting and price setting. In quantity setting, at first round, each individual bidder sends the valuations for the items which intend to procure. The auctioneer allocates provisional allocation to the requested items depending on bidding price and in the next rounds the bidders are able to adjust their bidding price. In price setting auctions, each bidder submits a bundle of items that desire to purchase based on auctioneer price and later through adjusting the price, demand and supply will be balanced (Dai & Chen, 2012).

Combinatorial auctions (CA) have been applied to truckload transportation. Chen (2003) used this auction in logistics domain as a mechanism of combining different items that one or more packages are bid by carriers. Providing better cost estimation on the probability of follow-on loads in packages lead to optimum transportation procurement. The general process of multi-round combinatorial auction (CA) is shown in figure 2.2.

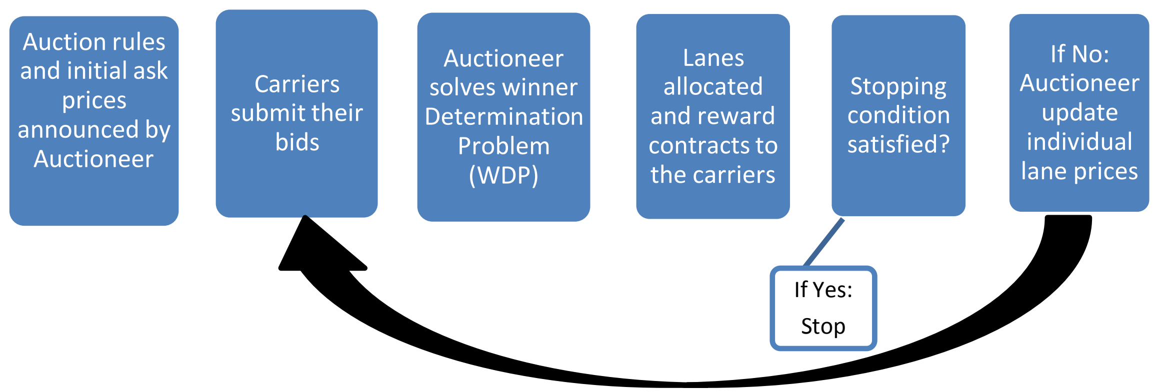

Figure 2.2: General process of multi-round combinatorial auction
(Kwon, Lee, & Ma, 2005)

In this thesis, an iterative combinatorial auction is applied in order to allocate proper bundles of orders to the carriers.

2.5 Auction-based carrier collaboration

Most of shippers use auctions to procure transportation services in a defined time window. Through combinatorial auctions approach their operating costs will reduce significantly and in the same time, unsuitable lanes will not allocate to the carriers. Large shippers procure their logistics services through requests for proposals (RFPs) procedure leading to one or two year contract. In this approach, transportation services are affected by economies of scope more than economies of scale.

Economy of scale is defined as decreasing transportation costs while the volumes on all lanes increase in the same proportion. Economies of scope defined as decreasing transportation costs while the set of lanes form a synergetic network collectively.

In other words, a carrier potentially considers a bundle of lanes that would have economies of scope where its revenue is more than the cost of servicing.

Combinatorial auction (CA) mechanism is applied by a large number of shippers and 3PL (Third Party Logistics) providers for reducing relevant costs. Combinatorial auction called also combinatorial bidding, combinatorial procurement or conditional bidding. The carriers asked to bid on a group of lanes rather than an individual lane, considering their hands-on orders and facilities (Sheffi, 2004). He also remarked some important issues in transportation procurement and presented how combinatorial auction is capable to cope with the challenges.

In TL transportation and decentralized setting, Kwon et al. (2005) proposed a multi-round combinatorial auction mechanism for truckload transportation procurement; the mechanism is integrated to the winner determination (WD) and bidder package optimization problem. A descending multi-round approach is used to identify a valuable lane package through solving an optimization problem. Each agent (carrier) bids for a package of lanes. This bidding mechanism is performed through solving an optimization model by the carriers in order to determine the best packages. Then, auctioneer computes a provisional allocation of lanes to carriers by solving a winner determination (WD) problem with the objective of minimizing costs of procuring transportation services. The results of mentioned mechanism revealed that both carriers and shippers reduce their cost through a better allocation system. In this study, transportation marketplace is modeled by multi-agent system and these agents share their capacities for obtaining a certain and common objective. Auction creates collaboration among agents. Shippers submit pick up-delivery jobs with timing constraints in a truckload mode through sequential auctions and carriers attempt to accomplish their jobs in a competitive environment. In another hand, two policies of delaying and breaking commitment are approved to maximize shipper profits in an auction.

In LTL (less than truckload) setting, Krajewska and Kopfer (2006a) proposed an auction model for collaboration among individual freight forwarding entities. Cooperating forwarders exchange their orders through a combinatorial auction (CA). The auction is individually rational, which means each individual partner increase its profit by participating in the coalition.

Effective collaboration among agents in a distributed system results in optimized utilization of resources. Therefore, greater efficiency and profit for the whole system will be obtained. However, before entering into the partnership, agents have to agree upon how to share the profit resulted from the collaboration. In a collaborative environment where, for example, carrier companies belong to a common holding organization, profit sharing may not require incentive compatible mechanisms.

Based on reviewed studies, in a large number of distributed transportation service networks a practical profit sharing mechanism ignored. In a centralized setting or in a situation that all carrier companies belong to holding organization, profit sharing is more practical rather than a decentralized approach.

An exchange mechanism is suggested by Ghjo, Schwind, and Vykoukal (2007), which is called ComEx and applied for inter-division of delivery orders in a logistics company directed by a profit center. Each cluster is a group of carriers, coordinated by a profit center that permit to outsource or insource the delivery contracts according to their geographical zones and time window in a way that whole profit of system is maximized. Then, each cluster will bid due to the renewed allocations and combinatorial auction, leads to minimization of total system. In this framework, a considerable profit will be gained and a potential mechanism needs to share the profit among the carriers. The success in exchange system depends on incentive for the profit centers to release delivery contracts into outsource process. Combinatorial auction (CA) mechanism is used to minimize total cost of transportation in a carrier collaboration system. The numerical experiment prove that logistics cost can drop by 14% by using ComEx system. However, it is not suitable setting where profit centers do not belong to a common holding organization and they may be reluctant to share their cost saving data. In this case, profit distribution mechanism and combinatorial auction is suggested.

What will be the advantages for a carrier company if transfer its contract to another company for optimizing another cluster profit and receive any other transportation contract? Absolutely, there is not any guarantee that shared profit compensates its loss.

In transportation services, there are a few proposed profit sharing models that distribute gained profit from a cost saving mechanism among the partners.

The idea of “Groupage” system is introduced by Krajewska and Kopfer (2006b). It is an overview about some profit sharing approaches, and referred to as request interchange among multiple forwarding companies to reach equilibrium between demand and transport resources. They presented a complete overview on studied sharing models: Loss sharing mechanism rather than profit sharing system. It is assumed that the unaccepted requests are always unprofitable that a central entity assign all these requests to an external forwarder (Schönberger ,2005), Schönsleben & Hieber (2004) proposed equally distribution of achieved profit among agents , Gomber, Schmidt and Weinhardt (1997) presented profit sharing with multi-agent auction approach where the agents bid on the requests, if serving a request make profit then it assumes as positive otherwise will be a loss situations. A bidder with the best price is chosen for performing the job. However, if a request shifted among partners, winner partner will pay second best bidder price. Finally, Krajewska and Kopfer (2006b) designed a profit distribution mechanism based on game theory and combinatorial auction. In this complicated model, each partner proposed the least cost of serving, called potential self-fulfilment of a request. A mapping of requests will be provided in a way that total profit of system is maximized. Each partner defines potential fulfilment cost for each bundle, and then combinatorial auction theory is applied to determine each set of optimal bundles. In profit sharing, the amount of obtained profit from request fulfilment will be shared among the partners.This study concludes that a decentralized system is technically feasible if it introduces a positive incentives to convince each independent agent to participate in a collaboration alliance.

Today, planning and scheduling are used in many services and manufacturing organizations. The function of scheduling relies on mathematical techniques which allocate limited resources to the jobs or activities.

Combinatorial auctions (CA) are used in scheduling and planning domain. Agnetis, Pacciarelli, and Pacifici (2007) proposed combinatorial auction models for scheduling problems. Combinatorial auction is used for generating the schedules, where a compromise schedule emanate via an iterative information exchange between bidders and auctioneer.

In context of scheduling, Kutanoglu and WU (1999) investigate a new method based on a distributed and autonomous environment. Combinatorial auction (CA) mechanism used to solve resource scheduling problem. In this research, a group of price-directed auction is introduced for distributed scheduling. Moreover, two auction mechanisms are considered: Auction protocols (non-adaptive Walrasian and adaptive tatonnemwnts) and two payment functions (regular and augmented tatonnements). Lagrangian relaxation method is applied for using subgradient search corresponds to an adaptive regular tatonnement.

Song and Regan (2003) proposed spot-market where a large number of shippers and carriers exchange their excess capacities. Spot-market ease exchange of information, increase convenience, drop transaction cost and design an environment in which both carriers and shippers access to larger markets. In current situation, a large number of transportation companies compete with a low profit margin and collaborating between these companies lead to gaining more profit. However, they are allowed to bid on combinations of loads and in case of negative utility, the carrier outsources order and the other carriers will bid concurrently. Winner determination (WD) problem is solved in a collaborative carrier setting to allocate the lanes to the bidder. In this study, the feasibility of using such auction mechanism and its benefits is examined. To the best of our knowledge, ignoring a benefit sharing system and pickup/delivery time window makes this research impractical for real situation.

The main focus of this thesis is on carrier collaboration problem in logistic services application. Multiple carriers compete in an auction-based environment to achieve delivery orders from a shipper to share their empty capacities in a competitive market. Our study can perform in both LTL (Less than truckload) and TL environment. In addition, proposed mechanism for reallocating requests among the carriers is an iterative combinatorial auction. A unique auctioneer is fixed to update (outsource) price of each request, the ultimate goal is maximizing total profit of the alliance. In another hand, each bidder (carrier) has to select the preferable bundles of orders subject to available capacities for profit maximizing based on announced initial price of auctioneer.

In this thesis two major components are used: Multi-agent system and combinatorial auction (CA). Instead of designing post-collaboration, a multi agent system is proposed in such a way that each carrier in carrier collaboration setting is assumed as a selfish agent and attempts to maximize own profit in an alliance. Moreover, multi-agent system is able to simulate high level of negotiation and cooperation in a daily basis tasks. On the other hand, auction addresses the reassignment of transportation requests and sharing achieved profit results in carrier collaboration.

Chapter 3

The Carrier Collaboration Problem

We consider a specific carrier collaboration environment in which multiple carriers collaborate by sharing a set of job orders. The objective is to reduce transportation costs across all carriers. In terms of economics, this objective is equivalent to maximizing social welfare of all carriers. Effective collaboration can reduce or eliminate empty backhauls, increase utilization rate of unoccupied capacity, and allow carriers to select their most cost effective routes. Therefore, overall transportation cost can be reduced.

In this chapter, we first give a description and a formulation of the carrier collaboration problem. The problem is formulated in a centralized sense, in which we assume that a central authority, such as a holding company of a group of carriers, has access to all required information to compute an optimal solution. After formulating the problem, we describe the possible procedures that can be used to assess the transportation cost of a carrier when taking a bundle of orders.

3.1 Description and Formulation

The Carrier Collaboration Problem (CCP) consists of a group of carriers and a shipper or group of shippers. The shipper has a set of available orders to be allocated to the carriers. The orders are specified by pickup/delivery time windows, pickup/delivery locations, and volume and weight to be shipped. Each carrier has a cost for each bundle of orders (the possible procedures to compute the cost are described later in this chapter). We assume that the cost of a bundle is the lowest price that a carrier would charge to ship the order. The problem is how to allocate orders to carriers in a way that the overall cost across all carriers is minimized.

Formally, a CCP consists of a set of n carriers $(i = 1, \dots, n)$. Let Ω be the set of all orders from a shipper or a group of shippers. For every bundle $B \subseteq \Omega$, $\mathrm{C_i(B)}$ is the cost of carrier i for shipping bundle B. An order j is defined as a five tuple

$< l_j^p, l_j^d, r_j, d_j, w_j, >$, where l_j^p is the pickup location ; l_j^d is the delivery location; r_j is the earliest possible time when the order is ready for shipping; d_j is the latest possible time by which the order is delivered; and w_j is the weight of the order.

Let $X_i(B) = 1$ if the bundle $B \subseteq \Omega$ is allocated to carrier i and zero otherwise.

The problem can be formulated as following integer programming.

$$Min \sum_{B \subseteq \Omega} \sum_{i=1}^{n} X_i\,(B) C_i(B) \qquad (1)$$

Subject to:

$$\sum_{B \subseteq \Omega} X_i(B) \ \leq 1 \qquad i = \ 1 \ldots \ \mathrm{n} \qquad (2)$$

$$\sum_{\mathrm{B} \ni j} \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{X_i}\,(\mathrm{B}) = 1 \qquad \forall \ j \ \in \ \Omega \qquad (3)$$

$$X_i\,(B) = \ \{0,1\} \qquad B \in \ \Omega\ , \ \ i = 1, \ldots, n \qquad (4)$$

The objective function (1) selects a solution that minimizes total cost of carriers. Constraints (2) ensure that at most one bundle could be assigned to each carrier; constraints (3) guarantee that each order is assigned to one carrier; and constraints (4) are a set of integer constraints.

3.2 Illustrative Examples of the Carrier Collaboration Problem

In this section, we present two illustrative examples of the CPP using the defined notations.

3.2.1 Example 1

The first example consists of three orders (O_1, O_2 and O_3) and two carriers (C_1 and C_2). The route network is fairly simple, which only has two nodes (a) and (b). The orders are specified as table 3.1.

Table 3.1: The specifications of three offered orders by a shipper (Example 1)

	Orders		
Order Configuration	O_1	O_2	O_3
w	4 T	2.5 T	15T
l^p	a	a	b
l^d	b	b	a
r	6 a.m.	3 a.m.	6 p.m.
d	1 p.m.	12 a.m.	12 a.m.

Table 3.2 presents all possible bundles of orders that these two carriers may select.

Table 3.2: All possible bundles of orders (example 1)

Bundle No.	Items	Bundle No.	Items
Bundle 1	O_1	Bundle 5	O_1, O_3
Bundle 2	O_2	Bundle 6	O_2, O_3
Bundle 3	O_3	Bundle 7	O_1, O_2, O_3
Bundle 4	O_1, O_2		

We assume the transportation cost of a bundle is computed by a carrier using the cost assessment procedure that will be described later in this chapter. The cost may vary between the carriers. Each of two carriers has his own transportation capacity and in hand orders from other shippers. In addition, home fleet is stationed in node (a) for both carriers. We assume that all carriers' fleet should return to their own station after shipping the order.

Table 3.3: Cost of two carriers for each bundle of order (Example 1)

Bundle No.	Carriers	
	Carrier1	Carrier 2
Bundle 1	400	360
Bundle 2	440	385
Bundle 3	440	442
Bundle 4	562	509
Bundle 5	932	653
Bundle 6	894	496
Bundle 7	1054	819

We have solved this example CCP using CPLEX. The solution shows bundle 7 is allocated to carrier 2 with the total cost of 819.

3.2.2 Example 2

The second example consists of four new orders (O_1, O_2, O_3 and O_4) and four carriers (C_1, C_2, C_3 and C_4) serving the orders .The route network is similar to example1, and for simplicity, two nodes of (a) and (b) is considered. Detailed orders' specifications are illustrated in table 3.4.

Table 3.4: The specifications of four offered orders (Example 2)

	Orders			
Order Configuration	O_1	O_2	O_3	O_4
w	7 T	10 T	8 T	8 T
l^p	a	a	b	b
l^d	b	b	a	a
r	6 a.m.	3 a.m.	6 p.m.	4 p.m.
d	1 p.m.	12 a.m.	12 a.m.	11 p.m.

All possible bundles of four submitted orders are shown in table 3.5.

Table 3.5: All possible order bundles of orders (Example 2)

Bundle No.	Items	Bundle No.	Items
Bundle 1	O_1	Bundle 9	O_2, O_4
Bundle 2	O_2	Bundle 10	O_3, O_4
Bundle 3	O_3	Bundle 11	O_1, O_2, O_3
Bundle 4	O_4	Bundle 12	O_2, O_3, O_4
Bundle 5	O_1, O_2	Bundle 13	O_1, O_2, O_4
Bundle 6	O_1, O_3	Bundle 14	O_1, O_3, O_4
Bundle 7	O_1, O_4	Bundle 15	O_1, O_2, O_3, O_4
Bundle 8	O_2, O_3		

Similar to example 1, the carriers follow cost assessment procedure which will be described in the next section. The cost of each bundle may vary across the carriers. Table 3.6 provides cost of carriers for each bundle of orders presented in Table 3.5.

Table 3.6: Cost of four carriers for each bundle of order (Example 2)

	Carriers			
Bundle No.	Carrier1	Carrier 2	Carrier 3	Carrier 4
Bundle 1	500	600	400	500
Bundle 2	600	500	600	400
Bundle 3	600	700	500	600
Bundle 4	700	600	700	600
Bundle 5	1300	1300	1400	1200
Bundle 6	1200	1100	1300	1200
Bundle 7	1000	1100	1200	1000
Bundle 8	1100	1000	1300	1500
Bundle 9	1300	1300	1300	1300
Bundle 10	1500	1400	1300	1300
Bundle 11	1700	1600	1500	1700
Bundle 12	1900	2000	1800	1800
Bundle 13	1600	1500	1500	1600
Bundle 14	1500	1600	1600	1600
Bundle 15	2200	2300	2100	2200

To solve CCP example, we have applied CPLEX and the result was obtained less than 30 seconds.

In the solution, bundle 14 is assigned to carrier1 and carrier 2 is selected to serve bundle 2 with the total shipping cost of 2000.

3.3 Cost Assessment of a Bundle of Orders

In CCP, a carrier is assigned to a bundle of orders as a package, and the objective is to minimize the overall costs across carriers. In this section, we describe how a carrier can assess the cost of a bundle. We also analyse the effect of key factors on carriers' shipping cost computing. Transportation cost of a bundle of orders includes (1) truck operating cost plus (2) cost of waiting time.

3.3.1 Truck operating cost

Recently, the motor carrier industry has become an interesting subject for cost analysis issues. In a truck cost analysis, the key factors that have significant effect on costs are listed as follows:

- Truck size (economies of scale)
- Working hours restrictions (due to some safety or regulation reasons)
- Road conditions
- Load availability (can be poor in some remote locations)
- Standard design of truck (effects on speed, fuel consumption rate, availability and price of spare parts)
- Labour, vehicles, spares and fuel costs that may vary from a place to another due to some uncontrollable factors such as: tax issues and local regulations
- Quality of service
- Delayed arrival of trucks and extra payment charge (due to unpredictable elements such as traffic and environment situations, cross border posts, etc.)
- Empty movement (in order to pick up the loads from customer's place, empty back-haul, or return to parking station).

3.3.1.1 Truck operating cost breakdown

Generally, truckers face to different prices, products characteristics, geographical zones, different spare parts with various qualities, driving practices and firm's size. Therefore cost estimating for a particular operator is difficult. For many efficient trucking operations typical trucks operating cost consists of variable and fixed costs. In the next section, we describe these two elements of operating cost.

3.3.1.1.1 Variable Costs

Variable costs or operating costs are the costs which are bounded to truck operation. These costs vary with travelled miles or the amount of driven hours. The main factors with considerable impact on a truck variable cost are listed as follows:

1) Fuel: One of the most effective factors in the modification of variable cost is fuel, easily computed by each individual. Fuel cost per kilometre equals to the volume of consumed fuel by each kilometre that a truck travels. The determinative elements are as follows: (Goodyear, 2008)
   - Vehicle's aerodynamics design
   - Speed rate
   - Load (for each 10 kips increment in load, fuel economy will drop by 5%).
   - Driving style
   - Wheel alignment and inflation pressure
   - Environnemental conditions
2) Labour: the labour cost is calculated as labour rate per mile or per hour if someone is hired to operate the truck.
3) Tires: the cost of tiers is determined through dividing a set of tires cost by its expected life.
4) Maintenance, repair and spare parts costs: maintenance and repair costs are complicated to calculate. This type of cost happens in routine maintenance, wear and unexpected incidents such as road accidents and purchase of required spare parts. Generally, historical cost records are used to estimate this type of cost.

   In addition, the companies have different maintenance plans to keep their trucks in good conditions; the older model vehicles have higher and less predictable maintenance costs. These multiple cost plans have profound effects on final cost calculation of a truck cost for serving a bundle.

3.3.1.1.2 Fixed Cost

Fixed cost is referred to the cost that does not vary in total when level of a truck operation changes.

Fixed cost includes the items which are listed below:

1) Licence fees insurance and sales tax: this item is a factor of trade area, travelled miles, weight, and product characteristics; and generally treated as fixed costs.
2) Management and overhead: including advertisement, communications, dispatching, and accounting costs.
3) Equipment:
   - Depreciation: depreciation is defined as the cost of a capital asset and calculated by subtracting the salvage value from purchase price and dividing it by estimated useful life.
   - ROI (Return on Investment): ROI is another portion of equipment cost. Interest on debt capital or return on equity investment costs are classified in this group.

We conclude that there are multiple plans and policies that a company may follow to operate its truck fleets. These various options will significantly affect the final computed cost (Hofstrand & Edwards, 2008).

Berwick & Farooq (2003) proposed truck costing software model to estimate truck costs under multiple conditions. Based on this study, fixed costs form around 66 % and variable costs form around 34% of final truck operating cost, while the major item in variable cost is fuel with portion of 37% and main item in fixed cost is equipment cost with 53%. By assuming the average operating cost of a TL (truckload) for a 20-T truck around $1.53 per km, the portion of fixed and variable costs would be $1 (66% of total cost) and $0.53 (34% of total cost), respectively.
On the other hand, truck empty movement is a kind of resource wasting. The operating cost of an empty 20-T truck drops by 10 % comparing with a full truck movement. Fuel cost and tires depreciation play important roles in the cost reduction of an empty truck. (Logistics Solution Builders, 2005)

3.3.2 Waiting time cost

Waiting time or idle time is referred to a non-productive time of a truck that occurs due to any operation stoppage cause. There are several items that can be classified in waiting time category of a truck such as:

- Loading and unloading process
- Hub preparation
- Availability of required auxiliaries (for instance : lift truck)
- Availability of weighing equipment
- Driver's resting time
- Congested road during peak hours (also lead to increment of gas consumption)

Barton (2006) calculated the cost of waiting time for each straight truck. According to his computation waiting time cost is around $40.2 per hour. In this thesis, we deploy Barton's calculation for computing cost of waiting time.

Barton also calculated average price of two types of trucks in two road conditions. The result is shown in Table 3.7.

In our calculation, we set transportation price of a 20-T truck equal to $3.6 per kilometre as standard transportation price.

Table 3.7: Average price / kilometre for two truck types in two different roads conditions

	Price per Kilometre (USD)	
Truck Type	with congestion	without congestion
Straight	2.97	2.53
Tractor-Trailer	3.58	3.12

3.4 Bundle of Orders

In a regular basis, an auctioneer submits different orders that have to serve by multiple carriers. Each submitted order has a particular pick up and delivery locations, release and deadline time, weight, and travelled distance that revealed by auctioneer.

A bundle of orders is a package of orders chosen by a carrier. For each bundle of orders, carrier computes its serving cost that does not depend on the other carriers. It is important to note that a carrier's cost is fixed and is not a function of paid price. All carriers keep their costs as private information and do not reveal to other carriers or shipper.

3.4.1 Feasible Bundle of Orders

Given the initial price of orders, the carriers look for the bundles that not only achieve the least repositioning costs for their trucks, but also do obtain the most profit. The goal of carrier is to find an optimal trade-off between cost and revenue. However, carriers pay-off decreases when the cost of serving a bundle increases.

Utility of a package is defined as gained revenue from servicing a set of bundle of orders minus transportation costs; the objective of each carrier is maximizing its utility (Lee, Kwon, & Ma, 2007).

Given the capacity of a carrier, if the carrier cannot find a way to schedule its transportation capacity such that the time window, load and pickup, delivery destination requirements of a bundle can be satisfied, the bundle is not feasible to the carrier.

Based on description, we conclude that the carriers have different transportation costs for serving the same bundle of orders.

In example1, three possible scenarios associated to the carrier's cost computation for an order are described.

3.4.1.1 Example 1

Assume two carriers (C_1 and C_2) should serve orders (O_1, O_2) in a simple route between nodes (a) and (b).

The detailed specifications of the orders are shown in table 3.8.

Table 3.8: The specifications of two offered orders by a shipper (Example 1)

	Orders	
Order Configuration	O_1	O_2
w	10 T	12.5 T
l^p	a	b
l^d	b	a
r	2 a.m. (d1)[1]	3 p.m. (d1)
d	12 p.m. (d1)	1 a.m. (d2)[1]

1: d1: day 1, d2: day 2

Scenario 1

Although, the orders were similar for both carriers, the order bundle consists of O_1 and O_2 assigned to C_1 due to its lower cost. In fact, C_1 has another order in hand from other shipper that drops his round trip cost significantly (economy of scale). Table 3.9 shows specification of (O_0) awarded to C_1 by another shipper.

Table 3.9: The specifications of order O_0

	Configurations				
Order	w	l^p	l^d	r	d
O_0	10T	a	b	1 a.m. (d1)	11a.m.

Scenario 2

The impact of variable costs in carriers' final cost is notable. For example, if one of these two carriers utilizes a newer truck model in its transportation fleet, the cost of performing transportation service can be decreased due to reducing some variable costs such as following items:

- Fuel: the new truck models are fuel efficient for their aerodynamics design and high performance engines.
- Maintenance and spare parts: maintenance, repair and changing spare parts cost decrease significantly in new trucks models.

Scenario 3

Fixed cost is an important element that influences on the cost computing of an order by a carrier. A carrier with lower fixed cost can reduce significantly its transportation cost. Fixed cost varies due to one of the following reasons:

- Different locations have various license fees insurance price and sales tax.
- The number of trucks in a company's fleet decreases the overhead cost.
- In terms of ROI, each carrier may have a different amount of debt that impact on fixed cost

3.4.1.2 Example 2

In this section, we provide a cost computational example in which a carrier calculates the cost of bundles for three submitted orders include: O_1, O2 and O_3 by a shipper. For simplicity we assume a lane includes two nodes (a) and (b).

The cost assumption of this example is defined as table 3.10.

Table 3.10: The costs assumption (Example 2)

Item	Amount
Full truck load operating cost	1.53 USD/km
Empty truck operating cost	1. 37 USD /km
Waiting time cost	40 USD/ hr

Table 3.11 specifies the order configurations revealed by the shipper.

Table 3.11: The orders' configuration (Example 2)

	Orders		
Order Configuration	O_1	O_2	O_3
w	12.5 T	2.5 T	20T
l^P	a	a	b
l^d	b	b	a
r	2 a.m. (d1)	5 a.m. (d1)	8 p.m. (d1)
d	12 p.m. (d1)	3 p.m. (d1)	6 a.m. (d2)

The cost computation for all possible bundles of orders is provided as below.

Bundle1(O_1): $\left[\left(1.53 \times \left(\frac{12.5}{20}\right) \times 150\right) + \left(1.37 \times \left(\frac{7.5}{20}\right) \times 150\right) + (1.37 \times 150)\right] = 426\$$

Bundle2(O2): $\left[\left(1.53 \times \left(\frac{2.50}{20}\right) \times 150\right) + \left(1.37 \times \left(\frac{17.5}{20}\right) \times 150\right) + (1.37 \times 150)\right] = 414\ \$$

Bundle 3 (O3): $[(1.37 \times 150) + (1.53 \times 150)\ ] = 435\$\ \$$

Bundle 4 (O1, O2): $\left[\left(1.53 \times \left(\frac{15}{20}\right) \times 150\right) + \left(1.37 \times \left(\frac{5}{20}\right) \times 150\right) + (3\text{hrs} \times 40) + (1.37 \times 150)\right] = \$\ 549$

Bundle 5 (O1, O3): $\left[\left(1.53 \times \left(\frac{12.50}{20}\right) \times 150\right) + \left(1.37 \times \left(\frac{7.5}{20}\right) \times 150\right) + (8\text{hrs} \times 40) + (1.53 \times 150)\right] = 770\$$

Bundle 6(O2, O3): $\left[(1.53 \times (2.50/20) \times 150) + \left(1.37 \times \left(\frac{17.5}{20}\right) \times 150\right) + (5\text{hrs} \times 40) + (1.53 \times 150)\right] = 638\$$

Bundle7 (O1, O2, O3): $\left[(1.53 \times (15/20) \times 150) + \left(1.43 \times \left(\frac{5}{20}\right) \times 150\right) + (3\text{hrs} \times 40) + (5\text{hrs} \times 40) + (1.53 \times 150)\right] = 775\$$

We can conclude that actual cost for serving bundle of orders includes truck operating cost for empty or occupied truck capacity along with waiting time cost. In addition to the multiple described effective factors, business situation and company's policy have major impact on cost computing of a bundle of orders.

Chapter 4

An Iterative Bidding Framework for Carrier Collaboration

The carrier collaboration problem described in the previous chapter is a centralized formulation in which we have assumed that carriers' costs are known to the shipper. However, this assumption is not true in game theoretic settings where carriers do not belong to a single organization. In the game theoretic settings, carriers' costs are private information and carriers will behave strategically to maximize their own benefits.

In this chapter, we consider CCP as a decentralized decision making problem in the sense that actual carrier cost of delivering a bundle of orders is private information, which is not known to the optimizer. To deal with the decentralized nature of the problem, we adopt an auction-based approach. Recently, decentralized markets and distributed mechanisms absorbed plenty of research interests. In transportation application, agents are autonomous and capable to control their behaviours against a common goal. Decentralized solutions are defined as movement away from centralized solutions because of the ability to cope with a high degree of complexity and change. Lang et al (2008) advocated that decentralized solutions may be very appropriate where a centralized one is not feasible due to some practical constraints.

We propose an iterative bidding framework for the decentralized CCP. The framework provides a structure for the carriers and the auctioneer to interact in a systematic way and eventually evolve the provisional solutions towards an optimal or near optimal one. Iterative bidding also reduces carriers' information revelation and adds the potential of accommodating dynamic changes during the bidding process. The iterative bidding framework is a multi-attribute auction, which allows negotiation over price and a non-price attribute: a carrier's schedule. In addition, the framework has good privacy preserving properties. For example, unlike VCG auctions, it does not require carriers' to expose their capabilities, availabilities and configurations. Also, it does not require complete revelation of carriers' costs.

The proposed iterative bidding is a price-based combinatorial auction. The auctioneer can be the shipper or other management authority. In the rest of this chapter, we first present our auction procedure and then describe the winner determination model. Finally, a worked example is presented.

4.1 Initialization

Before bidding starts, the auctioneer presents the set of available orders to the carriers. Carriers select their set of feasible bundles named Ω_i . For each selected bundle subset of Ω_i , the carrier computes the cost described in cost assessment section. The cost of each bundle is calculated by each carrier independently and according to the policy of their companies. For each bundle of order, there is an initial price which is the maximum price that can be paid by the auctioneer for serving a bundle.

The initial bidding price for bundle of orders is set to be equal to initial price. Carriers are able to calculate their payoff for each bundle of Ω_i by knowing the initial price and computed cost, where payoff is initial price minus computed cost. To keep positive payoff, a carrier will decrease bidding price up to calculated cost to get the bundle. Then, carriers will choose the bundles with the highest payoff as selected bundles to start the bidding process.

4.2 Bidding Process

In each round of bidding I, one or group of carriers are awarded as provisional allocation. At the beginning of each round, carriers need to update their bidding prices. For the carriers which included in provisional allocation at round I-1, they can keep their bids' prices unchanged at round I. The carriers which are not awarded in provisional allocation have three updating options at round I: (1) Decrease their bidding price by ε on the bundle bid at round I-1 since the carriers are assumed to be rational in maximizing their payoff. ε, is the minimum decrement value fixed by the auctioneer. (2) Repeat bidding price at round (I-1). The carrier will be considered at final bid round and prohibited from increasing the bidding price on any of its bundles in following rounds. (3)The carriers can withdraw from bidding process.

After updating the price, each carrier needs to verify the set of bundles maximize its payoff. In other words, a carrier solve maximization problem $Max_{B\in\Omega_i}$ $[P_i^I(B) - C_i(B)]$,where $P_i^I(B)$ is the price of carrier i for bundle B at iteration I and $C_i(B)$ is the cost of carrier i for bundle (B).

After indicating a set of maximizing bundles, carrier will choose a bundle randomly and submit to the auctioneer with the updated bidding price. However, the carriers which entered in the final bid status are not allowed to increase their bidding price.

4.3 Bids Screening

After bids are received, the auctioneer starts screening the bids. The bids with the following specifications will not be considered in the winner determination procedure and named invalid bids: (1) any bidding price for a package higher than initial price at the beginning of the bidding procedure, (2) any bidding price for a same bundle which is higher than the highest bidding price received in previous rounds, and (3) decreased prices from carriers which entered at final status in previous rounds.

After the bidding terminates, the auctioneer implements final allocation and awards final carriers to serve the

4.4 Winner Determination Model (WDM)

Auctioneer has to solve the problem in the winner determination model in order to indicate the final winner or group of winners.

WDM selects a subset of submitted bids by carriers such that the total bidding price of all provisional allocations to be minimized.

Let n^I be the set of carriers submitted their bids at round I and $P_i^I(B)$ the bidding price of requested bundle (B) by carrier i and $i \in n^I$, then $X_i(B) = 1$ if the bundle $B \subseteq \Omega$ is allocated to carrier i , and zero otherwise.

The winner determination model can be formulated as following integer programming.

$$Min \sum_{i \in n^I} X_i \;\; P_i^I(B) \qquad (5)$$

Subject to:

$$\sum_{i \in n^I} X_i \leq 1 \qquad i = 1 \ldots \text{n} \qquad (6)$$

$$\sum_{\text{B} \ni j} \sum_{i \in n^I} \text{X}_\text{i}\,(\text{B}) = 1 \qquad \forall \; j \; \in \; \Omega \qquad (7)$$

$$\text{X}_\text{i} \; = \{0,1\} \, , i \in n^I \qquad (8)$$

The objective function (5) represents the total bidding price of all carriers for bundle (B) is minimized.

Constraints (6) ensure that awarded bids to each carrier in a provisional allocation do not exceed at most one bundle; constraints (7) guarantee that all submitted orders have to be assigned and constraints (8) are set of integer constraints.

4.5 Worked Example

This example consists of two orders O_1 and O_2 and three carriers C_1, C_2 and C_3.The route network is fairly simple with two nodes (a) and (b).

Each of these carriers has its own cost, which let them compute the payoff for each bundle. In addition, carrier's cost information is assumed as private information and will not reveal neither to the auctioneer nor to the rest of participants. It is obvious that the carriers which enter to the auction have positive payoffs. The cost of each carrier and initial price for the orders is presented in table 4.1.

In this worked example, cost assessment and price of order bundles of this example are not calculated based on real world cost assessment data presented in section 3.2. We aim to demonstrate multiple iterations procedure in combinatorial auction (CA) procurement. In order to limit the number of bidding rounds, initial prices are set close to the costs.

Table 4.1: Carriers' costs and auctioneer's initial price (worked example)

	Carrier 1			Carrier 2			Carrier 3		
	B1	B2	B3	B1	B2	B3	B1	B2	B3
Initial Price	100	150	250	100	150	250	100	150	250
Cost	60	90	150	50	90	210	40	80	190
Payoff	40	60	100	50	60	40	60	70	60

The carriers need to update their bidding prices and then submit the bundle with highest payoff during the auction process.

The objective is to minimize the total submitted bidding price by carriers or total procurement cost. It is assumed that minimum bidding price is the cost of a bundle computed by that carrier; therefore any of bidders will get a negative utility. In this example, the auctioneer sets ε equal to 20.

Iteration numbers, carriers' submitted bids and provisional allocation of each round are shown in table 4.2. In submitted bids column, (a, b, c) represents for carrier number, submitted bundle and carrier's bidding price of that bundle.

Table 4.2: Provisional allocation, auctioneer's cost and carrier's pay off in each round

Iteration	Submitted Bids	Provisional Allocation	Auctioneer Cost	Carrier's Payoff
1	(1,3,250),(2,2,150),(3,2,150)	(1,3)	250	100
2	(1,3,250),(2,1,100),(3,1,100)	(1,3)	250	100
3	(1,3,250),(2,2,130),(3,3,250)	(1,3)	250	100
4	(1,3,250),(2,3,250),(3,2,130)	(1,3)	250	100
5	(1,3,250),(2,1,80),(3,1,80)	(1,3)	250	100
6	(1,3,250),(2,2,110),(3,3,230)	(3,3)	230	40
7	(1,3,230),(2,3,230),(3,3,230)	(1,3)	230	80
8	(1,3,230),(2,1,60),(3,2,110)	(2,1), (3,2)	170	40
9	(1,2,150),(2,1,60),(3,2,110)	(2,1), (3,2)	170	40
10	(1,3,210),(2,1,60),(3,2,110)	(2,1), (3,2)	170	40
11	(1,1,100),(2,1,60),(3,2,110)	(2,1), (3,2)	170	40
12	(1,2,130),(2,1,60),(3,2,110)	(2,1), (3,2)	170	40
13	(1,3,190),(2,1,60),(3,2,110)	(2,1), (3,2)	170	40
14	(1,1,80),(2,1,60),(3,2,110)	(2,1), (3,2)	170	40
15	(1,2,110),(2,1,60),(3,2,110)	(1,2), (2,1)	170	30
16	(1,2,110),(2,1,60),(3,1,60)	(1,2), (2,1)	170	30
17	(1,2,110),(2,1,60),(3,3,210)	(1,2), (2,1)	170	30
18	(1,2,110),(2,1,60),(3,2,90)	(2,1), (3,2)	150	20
19	(1,3,170),(2,1,60),(3,2,90)	(2,1), (3,2)	150	20
20	(2,1,60),(3,2,90)	(2,1), (3,2)	150	20

WDM is applied to solve the worked example. The problem is solved by CPLEX in less than 7 seconds by implementing 20 rounds. Bundle 1 including O_1 is assigned to carrier 2, and carrier 3 is selected to ship bundle 2 consisting of O_2 with total shipping cost of 150.

Proposed combinatorial auction is an efficient auction design using an iterative bidding process. Moreover, a price mechanism is designed to direct the system. In this mechanism, carriers behave as self-interested agents with the objective of maximizing their own benefits while the overall performance of system is not considered. The procurement cost is the sum of bidding prices from awarded carriers at the final iteration round.

Chapter 5

Computational Study

In this chapter, we evaluate the proposed carrier collaboration framework through a computational study. Numerical experiments were carried out to test the performance of our proposed model.

5.1 Design of testing data

Since our main purpose is to evaluate the iterative bidding procedure, we intentionally assume a very simple route network which has only two nodes. However, the numbers of carriers and feasible bundles are at a realistic scale. In the design of testing data, it is assumed that there is also an initial price for each order and the price of a bundle is sum of these initial prices set by shipper. However, all the carriers which enter to the auction have positive payoffs and compete to get the most profitable bundles. The carriers' costs for each order were randomly generated from 0.4 to 0.8 of initial price of that order and assumed as private information which is hidden from other carriers and also auctioneer. 5 CCP groups of carriers are generated with the carrier numbers ranging from 20 to 300 (Table5.1). For each group, 4 instances are randomly generated and each generated instance consists of 8 orders (O_1, O_2, O_3, O_4, O_5, O_6, O_7 and O_8) which could be served between nodes (a) and (b).

Table 5.1: Number of carriers in each group

	Group				
	1	2	3	4	5
Number of carriers	20	60	100	160	300

Table 5.2 presents complete order configurations.

Table 5.2: Orders' specifications

Order	Configurations				
	w	l^p	l^d	r	d
O_1	2T	a	b	4 a.m. (d1)[1]	12 p.m. (d1)
O_2	3T	a	b	5 a.m. (d1)	1 p.m. (d1)
O_3	5T	a	b	6 a.m. (d1)	2 p.m. (d1)
O_4	2T	a	b	6 a.m. (d1)	2 p.m. (d1)
O_5	5T	b	a	4 p.m. (d1)	12 a.m. (d1)
O_6	5T	b	a	5 p.m. (d1)	1 a.m. (d2)[1]
O_7	2T	b	a	6 p.m. (d1)	2 a.m. (d2)
O_8	3T	b	a	6 p.m. (d1)	2 a.m. (d2)

1: d1: day 1, d2: day 2

The CCP auction-based model is evaluated in terms of procurement cost performance and quality of solution under various bundles of orders level imposed by shipper. For computational study, three levels are defined: Configuration 1 consists of 8 orders and 5 bundles, configuration 2 consists of 8 orders and 12 bundles, and configuration 3 consists of 8 orders and 20 bundles (Table 5.3). For each group of instances, optimal solution value is computed by solving CCP integer programming model presented in chapter 3.

Table 5.3: Three levels of configurations

Configuration #	Number of Orders	Number of feasible bundles
1	8	5
2	8	12
3	8	20

5.2 Experimental results

The CCP model is coded in CPLEX and 5 groups of instances problems are solved. The solutions derived from auction-based model are compared against optimal computed results. In table 5.4, first column of each configuration shows the average optimal solution for 5 groups of testing problems. The second column shows the carrier cost and the third column is procurement cost computed by the auction-based model. The value of ε is set to 100 for all biddings.

Table5.4: Optimal cost, carrier cost and procurement cost generated at different configurations

Group	Configuration #1			Configuration # 2			Configuration # 3		
	Optimal cost	Carrier cost	Procurement cost	Optimal cost	Carrier cost	Procurement cost	Optimal cost	Carrier cost	Procurement cost
1	2742	3132	3250	2647	3092	3150	2590	2873	3050
2	2710	2796	2950	2620	2730	2900	2590	2608	2850
3	2544	2782	2850	2485	2750	2800	2468	2678	2750
4	2530	2742	2750	2419	2647	2750	2379	2565	2650
5	2441	2572	2700	2401	2500	2650	2367	2475	2550

It is observed that, on average, optimal cost in configuration 2 and 3 decreased to 96 % and 95.5 % and procurement cost decreased to 98 % and 95 % of those in configuration 1.

The procurement cost performance of configuration 1 is shown in figure 5.1.The graph shows the average procurement cost increase around 12% against optimal solution.

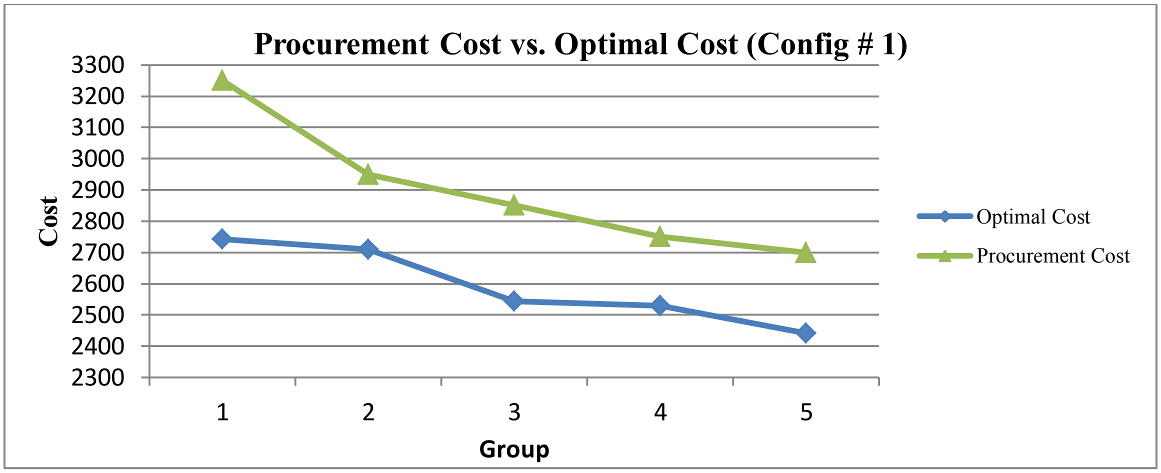

Figure 5.1: Procurement Cost vs. Optimal Cost for configuration 1

Figure 5.2 and 5.3 depict rise of 13 % and 12 % of procurement cost against optimal cost at configurations 2 and 3, respectively. It is clearly seen that increased competition among multiple carriers could cause a significant decrease in procurement cost.

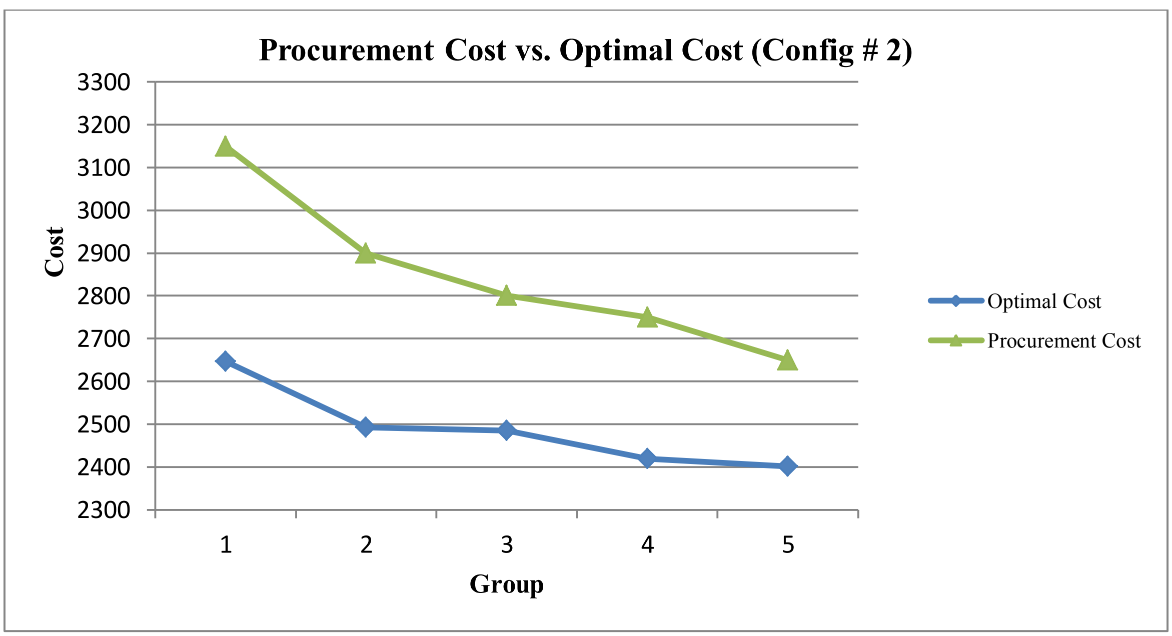

Figure 5.2: Procurement Cost vs. Optimal Cost for configuration 2

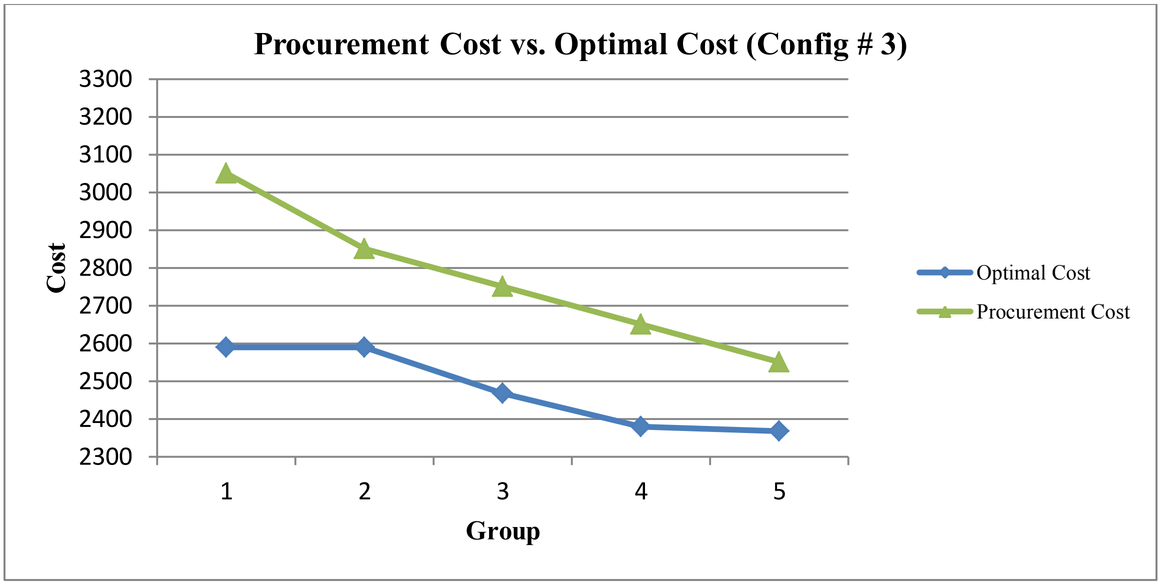

Figure 5.3: Procurement Cost vs. Optimal Cost for configuration 3

In addition, average carrier cost increased around 8 % against optimal cost at configuration 1, and for the same comparison at configuration 2 and 3, 9 % and 6.5 % were computed.

It is evident from the experimental results that increased competition among multiple carriers in both carriers' quantities and number of bundles dimensions, can significantly increase procurement cost performance and quality of solution.

5.3 Effect of epsilon on cost performance

In this section, we study the effect of multiple values for minimum decrement, epsilon (ε), on a worked example to illustrate sensitivity of auction results for different decrements.

5.3.1 Worked example

The example includes six different orders include O_1, O_2, O_3, O_4, O_5 and O_6 and 65 carriers consist C_1, C_2 … C_{65} , which classified in 3 different groups. For simplicity, we assume a lane includes only two nodes (a) and (b) and all trucks are stationed at node (a) and have to return to their stations after completing the services.

Table 5.5 presents available orders specifications.

Table 5.5: Order specifications

	Configurations				
Order	w	l^p	l^d	r	d
O_1	2T	a	b	5 a.m. (d1)	3p.m. (d1)
O_2	3T	a	b	6 a.m. (d1)	4p.m. (d1)
O_3	5T	b	a	10 p.m. (d1)	8a.m. (d2)
O_4	6T	b	a	12 p.m. (d2)	10a.m. (d2)
O_5	6T	b	a	12 p.m. (d2)	10a.m. (d2)
O_6	5T	b	a	1 a.m. (d2)	11a.m. (d2)

The carriers are classified in 3 different groups: group1 consists of C_1 to C_{20} and bid for 3 bundles of orders, group 2 includes C_{21} to C_{45} with 5 bidding bundles and group 3 includes C_{46} to C_{65} and bid for 6 bundles of orders. The costs of carriers for each order were randomly generated from 0.4 to 0.8 of initial price of that order. All 65 carriers participate in the auction. The procurement cost is the final bidding price determined by market competition at the termination of the auction. Each bundle has an initial price equals to sum of initial prices of the orders contained in each bundle. For decentralized framework, we applied CCP auction-based model in CPLEX. The value of ε is set to 30 for all biddings. The results are summarized in table 5.6 which is computed by running 269 iterations.

Table 5.6: Decentralized result

Winner	Assigned Orders	Procurement cost	No. of Iterations
C10	(O_2, O_5)	690	269
C16	(O_1, O_3, O_4, O_6)	1470	
	Total procurement cost	2160	

For observing effect of ε on the results, the value of minimum decrement is generated ranging from 50 to 700.

5.3.2 Epsilon and total procurement cost

Intuitively, the smaller the value of epsilon, the lower bidding price in final round is expected. In figure 5.4, procurement costs fluctuation is considered. However, if we graph a trend line (based on a regression analysis of cost as a function of epsilon), we see that average procurement cost tends to increase over epsilon increment.

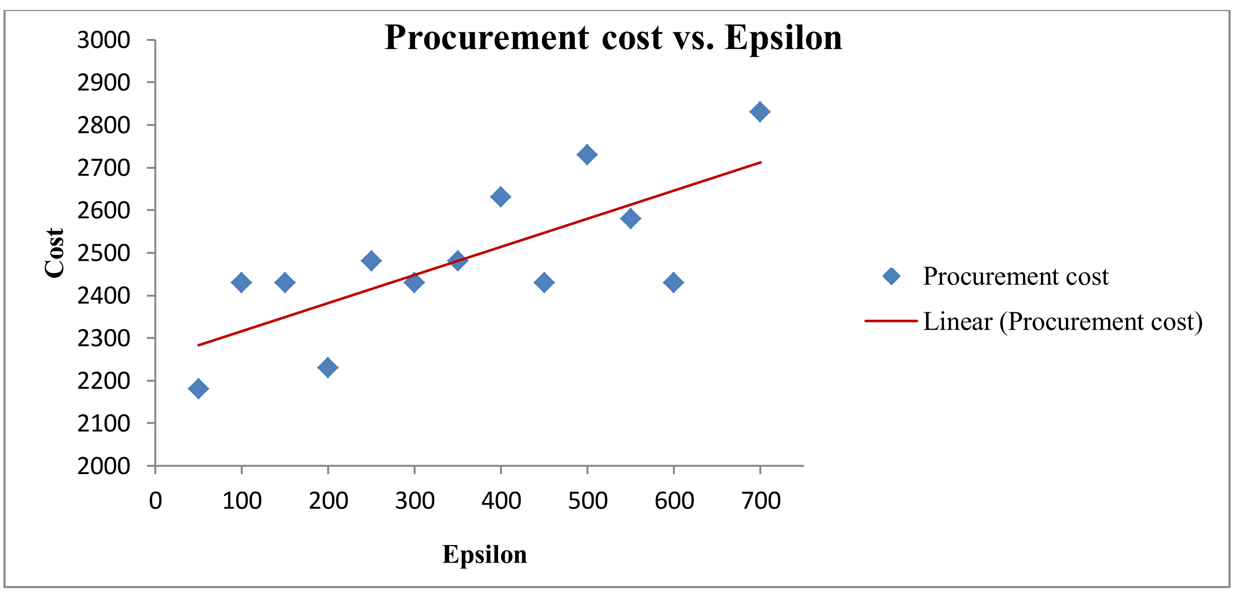

Figure 5.4: Effect of epsilon on total procurement cost

5.3.3 Epsilon and number of iterations

Epsilon has direct impact on number of iterations. In order to experiment the impact, we applied different epsilon values and concluded by increasing epsilon, the number of iterations decreased (Figure 5.5).

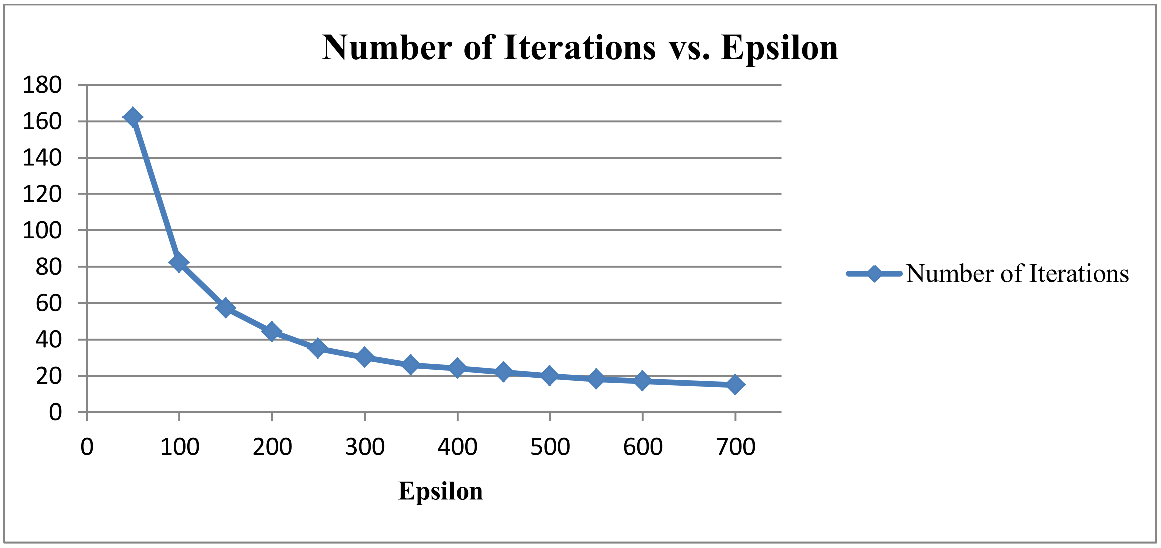

Figure 5.5: Effect of epsilon on number of iterations

5.3.4 Epsilon and processing time

We use figure 5.6 to demonstrate effect of epsilon changes on processing time. Clearly, processing time decreases dramatically by increasing epsilon value.

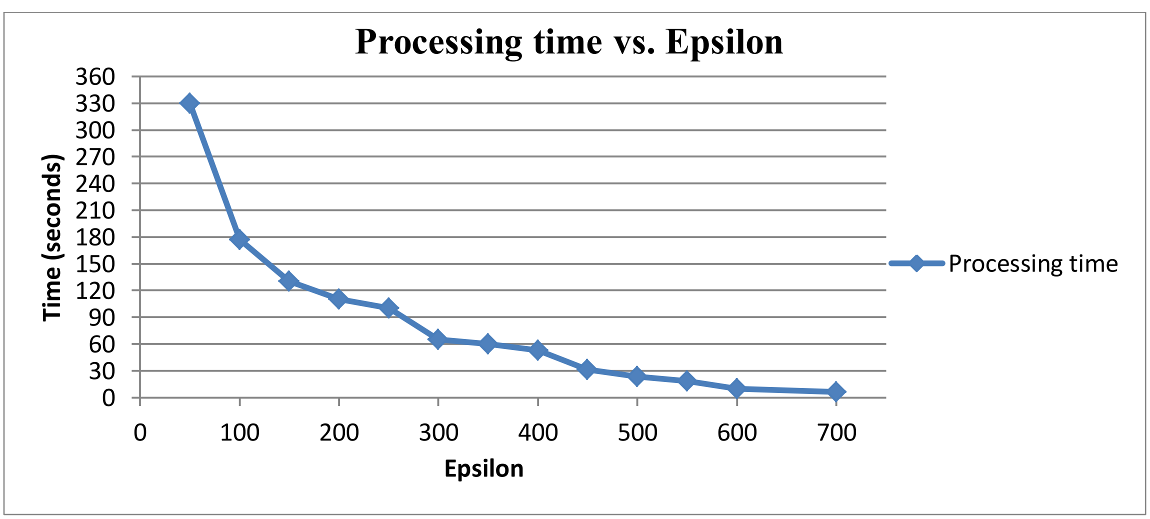

Figure 5.6: Effect of epsilon on processing time

It is concluded that the results of our proposed model for decentralized approach are close to centralized coordination. For computational study, three configurations were defined. The procurement cost performances for configuration 1, 2, and 3 are 88%, 87%, and 88%. In addition, the quality of solution for the same configurations is computed equal to 92%, 91%, and 93.5%, respectively.

Chapter 6

Summary and Conclusions

This thesis investigates modeling and computational issues in developing solution approaches to decentralized problems in logistics services. Our objective is to design economic-based models capable of coordinating the resource allocation behaviors of independent entities in decentralized environments. This chapter summarizes the main contributions of this thesis, highlights our conclusions, and presents some future research directions.

This study analyzes carrier collaboration challenges in transportation services. Although numerous studies have been conducted in application of combinatorial auction (CA) in transportation service procurement, there is a lack of study where the winner determination is bounded with bidder optimization through bundle of orders derived from a current allocation at each round. Descending combinatorial auction designed for transportation services procurement involves challenges for both shippers and carriers. In this thesis, we studied an integrated multi-round combinatorial auction design considering carriers' private information. Transportation services are inherently distributed and agent-based systems can be appropriate approaches due to carriers distributed and autonomous nature. In chapter 4, we proposed a practical auction –based CCP model for decentralized framework. To demonstrate the application of the proposed models, we provide the numerical experiments in a realistic scale.

The results of the study confirm that collaboration is beneficial. In terms of shipper, procurement cost decrease and also all orders will be served by the carriers. On the other hand, carriers are able to select feasible bundles of orders considering availability of transportation fleets, orders from other shippers, and the rest of restrictions. Moreover, in the proposed model, multiple carriers can collaborate to optimize their transportation operation through sharing unoccupied capacities of vehicle and delivery requests in a dynamic environment.

On the basis of the results of the numerical experiments, it can be concluded that procurement costs computed by the proposed model are very close to the optimal one derived from centralized framework. Besides, the increased competition among multiple carriers in terms of quantities and bundles of orders can significantly increase procurement cost performance and quality of solutions.

The main result drawn from this thesis proves that collaboration among multiple carriers in an agent-based system can be implemented through a right combinatorial auction (CA) design.

We have assumed the route network is fairly simple and only has two nodes. In real situations, transportation alliance expand to bundles of lanes consists of multiple origins and destinations. In terms of capacity, a good flexible response model is critical to handle multiple capacities while in our proposed model, all the trucks are identical. We will continue working along this direction. One of our future research topics is adding several nodes to serving network and designing more realistic routes. To make the model more practical, we will also consider different capacities for the trucks in LTL (Less Than Truckload) transportation mode.

References

Agarwal, R., & Ergun, O. (2008). Mechanism Design for a Multicommodity Flow Game in Service Network Alliance. *Operations Research Letters, Volume 36, No.5*, 520-524

Agnetis, A., Pacciarelli, D., & Pacifici, A. (2007). Combinatorial models for multi-agent scheduling problems. *Multiprocessor Scheduling, Theory and Applications, I-Tech Education and Publishing,* 21-46

Barton, R. (2006). Estimation of Costs of Heavy Vehicle Use Per Vehicle - Kilometre in Canada . *Transportation Canada Economic Analysis Directorate, File T8080-05-0326*

Berger, S., & Bierwirth, C. (2009). Solutions to the request reassignment problem in collaborative carrier networks.*Transportation research Part E, Volume 46, No.5*, 627-638

Berwick, M., & Farooq, M. (2003). Truck Costing Model for Transportation Managers. *Upper Great Plains Transportation Institute, North Dakota State University*

Biswas, S. (2004). *Design of Iterative Mechanisms for Combinatorial Auctions and Exchanges.* Ph.D thesis, Indian Institute of Science, Engineering in Computer Science & Automation

Chen, X. (2003). *Transportation Service Procurement using Combinatorial Auctions.* Master thesis. Massachusetts Institute of Technology

Dai, B., & Chen, H. (2009). Mathematical model and solution approach for collaborative logistics in less than truckload (LTL) transportation. *39th International Conference on Computers & Industrial Engineering, Troyes, France,* 767-772

Dai, B., & Chen, H. (2012). Price-setting based Combinatorial Auction Approach for Carrier Collaboration in Pickup and Delivery Service. *Submitted to IEEE Transaction on Automation Science and Engineering*

Ergun, O., Kuyzu, G., & Savelsbergh, M. (2007 a). Reducing Truckload Transportation Costs Through Collaboration. *Transportation Science, Volume 41*, 206-221

Ergun, O., kuyzu, G., & Savelsbergh, M. (2007 b). Shipper Collaboration. *Computers Operation Research, Volume 34, No.6,* 1551-1560

Fischer, K., Müller, J. P., & Pischel, M. (1995). Cooperative transportation scheduling: an application domain for DAI. *Journal of Applied Artificial Intelligence,Volume 10,*1-34

Ghjo, O., Schwind, M., & Vykoukal, J. (2007). The Design of Incentives in a Combinatorial Exchange for Intra-Enterprise Logistics Services. *The 9 th IEEE International Conference on E-Commerce*

Gomber, P., Schmidt, C., & Weinhardt, C. (1997). Elektronische Märkte für die dezentrale Transportplanung. *Wirschaftsinformatik 39(2)*, 137-145

Goodyear. (2008). *Factors affecting Truck Fuel Economy*. Retrieved from http://www.goodyear.com/truck

Hofstrand, D., & Edwards, W. (2008). Motor Vehicle Cost. *IOWA State University*

Houghtalen, L., Ergun, O., & Sokol, J. (2007). Designing Allocation Mechanisms for Carrier Alliances. *Industrial and Systems Engineering, Georgia Institute of Technology*

Kalagnanam, J., & Parkes, C. (2004). *Auctions, bidding, and exchange design. Handbook of Quantitative Supply Chain Analysis:Modeling in the E-Business Era,* 143-212

Krajewska, M., & Kopfer, H. (2006 a). Collaborating freight forwarding enterprises: Request allocation and profit sharing. *OR Spectrum, Volume 28, No.2*, 301-317

Krajewska, M., & Kopfer, H. (2006 b). Profit sharing approaches for freight forwarders: An overview. *Proceedings of 5th International Conference on Modern Trends in Logistics*,157-161

Kutanoglu, E., & WU, S. (1999). On combinatorial auction and Lagrangean relaxation for distributed resource scheduling. *IIE Transaction, Volume 31, No.9,* 813-826

Kwon, R., H., Lee, C., & Ma, Z. (2005). An integrated combinatorial auction mechanism for truckload transportation procurement. *Technical Report, Mechanical and Industrial Engineering, University of Toronto, Ontario, Canada*

Lang, N., Moonen, H. M., Srour, F. J., & Zuidwijk, R. A. (2008). Multi Agent Systems in Logistics: A Literature and State-of-the art Review. *ERIM Report Series,* Reference No. ERS-2008-043-LIS

Langley, C. (2000). *7 Immutable Laws of Collaborative Logistics*. Retrieved from http://www.idii.com/wp/7ImmutableLaws.pdf

Lee, C., Kwon, R., & Ma, Z. (2007). A carrier's optimal bid generation problem in combinatorial auctions for transportation procurement. *Transportation Research Part E, Volume 43, No.2,* 173-191

Logistics Solution Builders. (2005). Operating Costs of Trucks in Canada 2005. *Transport Canada, File No. T 8080-05-0242*

Mes, M., Heijden, M., & Harten, A. (2007). Comparison of agent-based scheduling to look-ahead heuristics for real-time transportation problems. *European Journal of Operational Research, Volume 181*, 59-75

Moore, E., Warmke, J., & Gorban, L. (1991). The Indispensable Role of Management Science in Centralizing Freight Operations at Reynolds Metals Company. *Interfaces, Volume 21,* 107-129

Nadarajah, S. (2006). *Strategic Freight Transportation Contract Procurement.* Ph.D thesis. University of California, Irvine

Nadarajah, S., & Bookbinder, J. (2007). Enhancing Transportation Efficiencies through Carrier Collaboration. *BPC World Conference Proceedings*

Ozener, O., Ergun, O., & Savelsbergh, M. (2007). Collaboration for Truckload Carriers. *Submitted for Transportation Science*

Rangavittal, G. (2008). *The Impact and Dynamics of Centralization in Supply Chain Decision-making.* Master thesis. Massachusetts Institute of Technology

Robu, V., Noot, H., La Poutre, H., & Schinjndel, W. (2011). A multi-agent platform for auction-based allocation of loads in transportation logistics. *Expert Systems with Applications, Volume 38*, 3483-3491

Schonberger, J. (2005). *Operational Freight Carrieer Planning.* Berlin , Springer

Sheffi, Y. (2004). Combinatorial Auctions in the Procurement of Transportation Services. *Interfaces,Volume.34* , 245-252

Song, J., & Regan, A. C. (2003). An Auction Based Collaborative Carrier Network. *Technical report: UCI-ITS-WP-03-6, Institute of Transportation Studies, University of California, Irvine*

Sutherland, J. (2006). Collaborative transportation management: A solution to the current transportation crisis. *Leigh University Center for Value Chain Research Pennsylvania, USA*

Appendix I

CCP integer programming model, coded in ILOG CPLEX for Centralized approach

```
tuple order
{
     int orderid;
  }

tuple carrier
{
    key int carrierid;

}

tuple package
{
     key int packageID;
     {int} items;
}

{order} orders=...;
{carrier} carriers=...;
{package} packages=...;

int cost[c in carriers][p in packages]=...;


dvar boolean X[c in carriers][p in packages];


minimize sum (c in carriers, p in packages)(X[c][p]*cost[c][p]);
 // objective function

subject to
{

forall(c in carriers)sum(p in packages) (X[c][p])<= 1;
//Guarantee that each carrier can get only one package

forall (d in orders) sum(c in carriers,k in packages: d.orderid in
k.items)X[c][k]==1 ;
// Ensure that for all orders included in packages,one carrier will be
assigned
}
execute Writedata
{
      writeln(X);
```

Appendix II

Winner determination model, coded in ILOG CPLEX (Decentralized Coordination)

```
tuple Order
{
      key string OID;
      int initialPrice;
}

tuple OrderBundle
{
      sorted{string} ordIds;
}
tuple Carrier
{
      key string CID;
      int reqPrice;
      OrderBundle re;
      int win;
}


tuple list
{
      key OrderBundle re  ;
      int initialPrice;
      int price;
      int cost;
}


//{orderType}ordertypes=...;
{Carrier}carriers=...;
{Order} orders=...;
{list} lists[carriers]=...;
{OrderBundle} Bunion;
//{package} packages=...;




execute choosing_bundle
 {
      var ncarriers=carriers.size;
      for(var c=1; c<= ncarriers; c++)
      {
             var temp = carriers.get("CID"+c);
      //     writeln("current temp:")
    //     writeln(temp);
    //     writeln(" ");
```

```
            if(temp.win !=1)
            {
                  var epsilon = 60 ;
                  if(temp.re.ordIds.size>0)
                  {
                     var oldtemp = lists[temp].get(temp.re);
                     oldtemp.price=oldtemp.price-epsilon;
                   }
                   temp.re.ordIds.clear();

                  var utility=0;
                  var index;
                  for(var l in lists[temp])
                  {
                       if(l.price-l.cost > utility)
                     {
                             utility=l.price-l.cost;
                             index=l;
                       }
                }


                 if (utility > 0)
                  {
                       for (var i in index.re.ordIds)
                        {
                             temp.re.ordIds.add(i) ;
                        }
                  }
                 if (temp.win==-1)
                  {
                       temp.win=0 ;
                       temp.reqPrice=index.price;
                  }
            }

      //writeln("temp:"+ c +" "+ temp);
       }
      writeln("carriers: " +carriers);
   }
execute Union_initiation
{
      for(var c in carriers)

            Bunion.add(c.re);
            writeln("Union: "+Bunion);
}


dvar boolean X[j in carriers];

minimize sum (j in carriers:(card(j.re.ordIds)>0) , l in
lists[j])(X[j]*(item(lists[j],<j.re>).price));

//maximize sum (j in carriers, l in
list[j])(X[j]*(item(list[j],<j.re>).initialPrice -
(item(list[j],<j.re>).price)));
```

```
subject to
{

forall (O in orders)
     sum(c in carriers: O.OID in c.re.ordIds) X[c] ==1 ;

forall(c in carriers) X[c]<= 1;
}

execute assign
{
    var psum = 0
    var vsum = 0
      for( var c in carriers)
      {
            if(X[c]==1)
            {
                c.win==1;
                  writeln("Carrier " + c.CID + " gets" + c.re + " with
price "+ lists[c].get(c.re).price);
                         psum = psum+lists[c].get(c.re).price;
                         vsum = vsum+lists[c].get(c.re).cost;

            }
      }
writeln ("Sum of Prices" + psum);
writeln ("Sum of Costs" + vsum);
}
```

Iterative Code for Winner determination model

```
main
{
      var log = new IloOplOutputFile("logfile.dat");
      for(var i = 1; i <= 5000 ; i++)
      {
            writeln("round: " + i);
            log.writeln("-------------round: " + i+ "------------------
---");

            var Source = new IloOplModelSource("New New .mod");
            var def = new IloOplModelDefinition(Source);
            var Cplex = new IloCplex();
            var opl = new IloOplModel(def,Cplex);
            var data = new IloOplDataSource("NE"+ i + ".dat");
            opl.addDataSource(data);
            opl.generate();
            Cplex.solve();

      /////////////////////////////////
      var ncarriers= opl.carriers.size;
      for(var c1=1; c1<= ncarriers; c1++)
      {
            var temp1= opl.carriers.get("CID"+c1);
```

```
            if( temp1.re.ordIds.size>0)
            {
                  var current1 = opl.lists[temp1].get(temp1.re);
                  var Cur_utility= current1.price-current1.cost;
                  log.writeln("Customer "+temp1.CID+" requests "+
temp1.re+ " with utility " + Cur_utility);
            }
      }
      log.writeln("X= " + opl.X);
      var CostSum=0;
      var PriceSum=0;
      for(var c2=1; c2 <= ncarriers; c2++)
      {
            var temp= opl.carriers.get("CID"+c2);
            temp.win = opl.X[temp];
            if(temp.win==1)
            {
                  var current = opl.lists[temp].get(temp.re);
                  log.writeln("Carrier " + temp.CID + " gets" + temp.re
+ " with price " + current.price+ " and cost " + current.cost);
                  CostSum= CostSum+current.cost;
                  PriceSum=PriceSum + current.price;
            }

      }
      log.writeln("Total Cost of Shipper : " + PriceSum);
      log.writeln("Total Bidding Price: " + PriceSum);
      log.writeln("Total Cost of Carriers: " + CostSum);
      log.writeln("________________round "+i+ "
finished________________________");


///////////////////////////////////////////////////////////////////////
/////////////////////




            var next = new IloOplOutputFile("NE"+(i + 1)+".dat");
            next.writeln("carriers=");
            next.write(opl.carriers);
            next.writeln(";");

            next.writeln("orders=");
            next.write(opl.orders);
            next.writeln(";");

            next.writeln("lists=");
            next.write(opl.lists);
            next.writeln(";");

            var allAssigned= true;
            for(var c in opl.carriers)
            {
                  if(c.win ==0)
                  {
```

```
                allAssigned=false;
                break;
            }
        }
        if(allAssigned==true)
            break;

        var noRequest= true;
        for(var c3 in opl.carriers)
        {
            if(c3.win==0 && c3.re.ordIds.size > 0)
            {
                noRequest=false;
            }
        }
        if(noRequest==true)
        {
            break;
        }


    }

}
```

Appendix III

Data Generator Code for Experiment

```
clc; clear;
N_o = 6;
N_c = 20; 25; 20
N_b = 3; 5; 6
PER = zeros(N_b , N_c);
for k = 1:N_c;
    PER(:,k) = 1 + randperm(2^N_o - 1 , N_b).';
%     PER(:,k) = randperm(2^N_o , N_b).';
end;
%Ini_pr = ceil(100 * rand(N_o , 1))+1000;
Ini_pr = [600 700 750 800 650 730];
Bid_pr = Ini_pr;
COST = zeros(N_b , N_c);
for k1 = 1:N_o
    for k2 = 1:N_c;
        COST(k1,k2) = 0.4*Ini_pr(k1) + ceil(0.3*Ini_pr(k1)*rand);
    end;
end;
%COST = ceil(100 * rand(N_o , N_c));

a = (1:2^N_o)-1;
b = dec2bin(a);



%idx = 1;
for k1 = 1:N_c
    STR = '{';
    for k2 = 1:N_b
        SUM = 0;
        SUM_int_pr = 0;
        str = '<{';
        for k3 = 1:N_o
            if b(PER(k2,k1),k3) == '1'
                str = [str, '"OID', num2str(k3), '"'];
                SUM = SUM + COST(k3,k1);
                SUM_int_pr = SUM_int_pr + Ini_pr(k3);
            end;
        end;
        str = [str, '} ', num2str(SUM_int_pr), ' ',
num2str(SUM_int_pr), ' ', num2str(SUM),'> '];
        STR = [STR, str];
    end;
    STR = [STR, '}'];
    disp(STR);
end;
```

APPENDIX IV

Agent-Based System Design Process Scheduling: Challenges, Approaches and Opportunities

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Agent-Based System Design for Service Process Scheduling: Challenges, Approaches and Opportunities

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Abstract Compared with traditional manufacturing scheduling, service process scheduling poses additional challenges attributable to the significant customer involvement in service processes. In services, there are typically no inventoried products, which make the service provider's capacity more sensitive to dynamic changes. Service process scheduling objectives are also more complicated due to the consideration of customer preferences, customer waiting costs and human resource costs. After describing the Unified Services Theory and analysing its scheduling implications, this paper reviews the research literature on service process scheduling system design with a particular emphasis on agent-based approaches. Major issues in agent-based service process scheduling systems design are discussed and research opportunities are identified. The survey of the literature reveals that despite of many domain-specific designs in agent-based service process scheduling, there is a lack of general problem formulations, classifications, solution frameworks, and test beds. Constructing these general models for service process scheduling system design will facilitate the collaboration of researchers in this area and guide the effective development of integrated service process scheduling systems.

1 Introduction

Scheduling is a decision-making process which allocates limited resources to tasks over time while satisfying certain constraints and optimizing one or more objectives. Scheduling problems are common to many domains such as manufacturing and services. The number and variety of scheduling problem models is astounding. In spite of the various presentations, most of the models can fit into a four-element structure which consists of activities, resources, constraints, and objectives (Wang, 2007). Using the four elements, Wall (1996) defines general resource constrained scheduling problems as given a set of activities that must be executed, a set of resources with which to perform the activities, a set of constraints which must be satisfied, and a set of objectives with which to judge a schedule's performance, finding the best way to assign the resources to the activities at specific times such that all of the constraints are satisfied and the best objective measures are produced.

The scheduling problems in service settings can be somewhat different from those in manufacturing. As summarized in Pinedo (2009), in manufacturing an activity usually transforms a physical component and adds value to it; resources are typically referred to as machines and the configuration of machines;

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objectives are typically a function of the completion times, the due dates, and the deadlines of the jobs. In service settings an activity usually involves people. It can be, for example, a meeting that has to be attended by certain people, a flight that transports passengers, an operation that has to be done by a surgeon on a given day. Services usually require both physical and human resources. In addition, the operational constraints in services can take diverse forms. A typical type is capacity requirements. They are important in reservation systems, in timetabling of meetings as well as in transportation planning and scheduling. In service settings, additional factors such as personnel costs, customer waiting costs and customer preferences are often considered in the objective function.

The differences between manufacturing and service process scheduling are mainly derived from the fundamental characteristic which defines service processes. A service significantly involves customer inputs (Sampson & Froehle, 2006). In other words, in order for a service to be produced, a customer has to present personally or he/she has to present his/her belongings or information. Compared with classical manufacturing scheduling models, this significant involvement of customer inputs presents additional challenges including distributed and dynamic environments, the presence of private customer information and often considerably more complicated scheduling objectives (we will explain these challenges in details in the next section).

The objective of this paper is not to provide an extensive survey of general service process scheduling models, but to focus on the models that take an agent-oriented paradigm which, we believe, is suitable for tackling service process scheduling challenges given its strength on dealing with distributed, dynamic and complex environments. An earlier survey of multi-agent systems for manufacturing process planning and scheduling can be found in Shen et al. (2006). Detailed descriptions of classical service process scheduling models can be found in Pinedo (2009).

The rest of the paper is organized as follows. In Section 2, we first describe the Unified Services Theory (Sampson, 2001), which categorically defines services. We then analyze the challenges in service process scheduling system design in light of the theory. In Section 3, we provide a brief overview of traditional approaches to service process scheduling system design. In Section 4, we review literature on agent-based service process scheduling system design. Major design issues and research opportunities are discussed in Section 5. Section 6 concludes the paper.