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# Studies on Auction Mechanism and Bid Generation in the Procurement of Truckload Transportation Services

Ke Lyu

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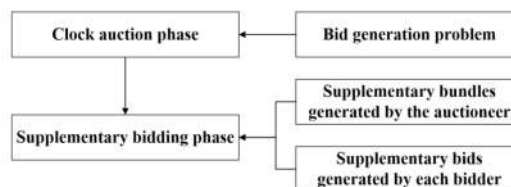
# Studies on Auction Mechanism and Bid Generation in the Procurement of Truckload Transportation Services



Truckload transportation  
with travel duration limited



Tranportation service procurement  
by auctions in electronic market



Two-phase combinatorial auction mechanisms

**Champ disciplinaire :**  
Sciences pour l'Ingénieur

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**THESE**  
*pour l'obtention du grade de*  
**DOCTEUR**  
**de l'UNIVERSITE DE TECHNOLOGIE DE TROYES**  
**en SCIENCES POUR L'INGENIEUR**

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*présentée et soutenue par*

**Ke LYU**

*Le 8 octobre 2021*

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**Studies on Auction Mechanism and Bid Generation  
in the Procurement of Truckload Transportation Services**

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## Résumé

Le transport par camions entiers est un mode courant de transport de marchandises, qui représente une part importante de l'industrie de transport, où les expéditeurs achètent des services de transport auprès des transporteurs. L'achat de services de transport est souvent réalisé par des enchères. Par concevoir des mécanismes d'enchères efficaces et des méthodes efficaces pour résoudre les problèmes de génération d'enchères associés, les expéditeurs et les transporteurs peuvent réduire leurs coûts et augmenter leurs bénéfices respectivement.

Cette thèse étudie trois problèmes soulevés dans l'achat de services de transport par camions entiers réalisé par une enchère combinatoire. Premièrement, deux mécanismes d'enchères combinatoires à deux phases sont conçus avec des paquets supplémentaires de demandes offerts à l'enchère générés respectivement par le commissaire-priseur et les transporteurs dans la deuxième phase. Deuxièmement, un algorithme de génération de colonnes est proposé pour résoudre le problème de génération d'enchères apparu dans l'enchère combinatoire. Enfin, le problème de génération d'enchères est étendu à un problème qui tient compte à la fois plusieurs périodes et l'incertitude dans l'achat de services de transport par camions entières. Ce problème d'optimisation stochastique est formulé par l'optimisation de scénario et l'équivalence déterministe. Pour résoudre ce modèle, une approche de décomposition de Benders est proposée.

**Mot clés:** transport de marchandises, vente aux enchères, problème de tournée de véhicules, optimisation combinatoire, programmation (mathématique)

## **Abstract**

Truckload transportation is a common mode of freight transportation, which accounts for a substantial portion of transportation industry, where shippers procure transportation services from carriers. Transportation service procurement is often realized by auction. Through designing effective auction mechanisms and efficient methods for solving related bid generation problems, shippers and carriers can save costs and increase profits respectively.

This thesis studies three problems raised in the procurement of truckload transportation services realized by combinatorial auctions. Firstly, two two-phase combinatorial auction mechanisms are designed with supplementary bundles of requests offered for bid generated by the auctioneer and the carriers respectively in the second phase. Secondly, a column generation algorithm is proposed to solve the bid generation problem appeared in the combinatorial auction. Finally, the bid generation problem is extended to one that considers both multiple periods and uncertainty in truckload transportation service procurement. This stochastic optimization problem is formulated through scenario optimization and deterministic equivalence. To solve this model, a Benders decomposition approach is proposed.

**KEYWORDS:** freight and freightage, auctions, vehicle routing problem, combinatorial optimization, programming (mathematics)

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## List of Abbreviations

BD	Benders decomposition
BGP	Bid generation problem
CA	Combinatorial auction
CCA	Combinatorial clock auction
ESPPRC	Elementary shortest path problem with resource constraint
LB	Lower bound
LCP	Lane covering problem
LTL	Less than truckload
MILP	Mixed-integer linear programming
RMP	Restricted master problem
SP	Subproblem
TL	truckload
TOARP	Team orienteering arc routing problem
TOP	Team oriteering problem
TSP	Transportation service procurement
UB	Upper bound
VRP	Vehicle routing probelm
WDP	Winner determination problem

## Glossary of Notations

$A_r$	Set of lanes included in route $r$
$H(H_k)$	Set of vehicles (of carrier $k$ )
$K$	Set of carriers (Chapter 3) / Set of scenarios (Chapter 5)
$L_r(L_t^r)$	Set of reserved lanes (in period $t$ )
$L_b$	Set of for-bid lanes
$L_t^p$	Set of probabilistic lanes in period $t$
$R$	Set of all possible routes
$T$	Set of all periods
$B$	Maximum travel duration of each vehicle
$c_{i,j}(c_{i,j}^k)$	Travel cost of lane $(i, j)$ (of carrier $k$ )
$d(d') (d_k(d'_k))$	Depot of the carrier ( $k$ )
$f_k$	Fixed cost of each vehicle of carrier $k$
$M$	Number of rounds so far in the clock auction
$P_{i,j}$	Outsourcing price given by the auctioneer of for-bid lane $(i, j)$
$R_{i,j}$	Revenue of serving reserved lane $(i, j)$
$t_{i,j}(t_{i,j}^k)$	Travel time of lane $(i, j)$ (of carrier $k$ )
$a_l^r (a_{i,j}^r)$	Binary variable which equals to 1 if lane $l$ or lane $(i, j)$ is in route $r$
$S_i^h (S_i^{k,h})$	Variable represents the time at which vehicle $h$ (of carrier $k$ ) leaves node $i$
$u_{i,j}^h$	Binary variable which equals to 1 if a reserved lane $(i, j)$ is served by vehicle $h$
$v_{i,j}^h (v_{i,j}^{k,h})$	Binary variable which equals to 1 if a for-bid lane $(i, j)$ is served by vehicle $h$ (of carrier $k$ )
$w_{i,j,t}(w_{i,j,t,k})$	Random variable which equals to 1 if probabilistic lane $(i, j)$ in period $t$ occurs (in scenario $k$ )
$x_{i,j}^h (x_{i,j}^{k,h})$	Binary variable which equals to 1 if vehicle $h$ (of carrier $k$ ) travels through lane $(i, j)$
$x_r$	Binary variable which equals to 1 if route $r$ is selected
$w_r$	Binary variable which equals to 1 if bundle $r$ wins
$z_l$	Binary variable which equals to 1 if lane $l$ is not contained in the winning bid

# 1 Introduction

## 1.1 Research background

Freight transportation plays an important role in economic and social life. In terms of economy, it is a major economic activity since households, businesses, and the government all consume transportation goods and services. In term of society, freight transportation connects producers and customers as well as provides many job opportunities. Due to different means of transportation, freight transportation is usually sorted as road, rail, air, maritime and inland waterways transportation, among which road transportation undertakes most of the transportation volume both in mileage and weight. According to the statistical data from relevant departments, in 2018 and 2019, the proportion of road transportation in total transportation exceeds 70% in American. China and most European countries (ATA, 2019; eurostat, 2018; MOT, 2019).

For road transportation, in consideration of how the transportation goods or requests are organized, there are two major categories of transportation, direct transportation and consolidated transportation (Caplice & Sheffi, 2006). These two categories are usually known as truckload (TL) transportation and less than truckload (LTL) transportation. In TL transportation, the goods in each request take up the entire space or capacity of each vehicle. This mode of freight transportation is commonly chosen when a shipper has enough goods to fill an entire truck, the goods are time-sensitive, or the shipper prefers the use of a dedicated truck to transport its goods. The benefit of truckload transportation is that the goods can be shipped directly from origin to destination, which guarantees the time efficiency of transportation while avoiding possible damages caused by repeatedly loading and unloading goods during a transportation process. LTL transportation is as opposed to truckload transportation. In less than truckload transportation, a vehicle may serve multiple requests simultaneously. During the service of one request, the vehicle may visit some other terminal to upload or download goods. Since truckload transportation takes up about 70% of total road transportation, this thesis focuses on TL transportation.

With the continuous development of market, both products and services pursue refinement. Manufacturers or distributors usually choose to outsource the transportation tasks to professional freight companies. That is, the shippers procure transportation services from the carriers. TL transportation market is fragmented,

competitive and operates on low profit margins, which makes transportation service procurement significant for both shippers and carriers to seek economic efficiency. For shippers, they want control costs and provide high level service to their customers. For carriers, they want to reduce empty vehicle repositions and operate efficiently. However, trucking consumes amounts of fuels as well as cause air and sound pollution. So, except for individual economic efficiency, social efficiency must be taken into consideration. In this context, a reasonable method is needed for the procurement of truckload transportation service.

The process that shippers procure transportation service for multiple requests from multiple carriers can be seen as an allocation problem (Lim et al., 2008). In other words, the shippers assign their transportation requests to a group of carriers. The allocation of these requests may be realized by a centralized approach or a decentralized approach. The centralized approach, which is based on a centralized mathematical programming model, requires the revelation of confidential cost information of the carriers and is thus not very practical. The decentralized approach, on the other hand, is a game playing between shippers and carriers and which include many different mechanisms. Among different decentralized approaches, combinatorial auction (CA) is strategic in the booming electronic trucking market (Caplice, 2007; Caplice & Sheffi, 2006).

Combinatorial auction is a representative auction-based mechanism for transportation service procurement which allows the carriers to bid for several requests at one time while the single item auction only allows a single request in the bid. This characteristic increases the efficiency of the auction, and then makes combinatorial auction more and more popular (Abrache et al., 2007; De Vries & Vohra, 2003). In combinatorial auctions, the auctioneer is on behalf of the shippers, and the bidders are the carriers who want to serve the transportation requests of the shippers. For the carriers, one advantage of combinatorial auction over the centralized approach is that they do not need to reveal their business data such as the existing contracts, transportation costs to serve the requests open for bid and the number of vehicles. Since combinatorial auction plays an important role in the procurement of transportation services, the mechanism for each combinatorial auction must be well designed to achieve efficiency.

Base on the number of rounds that processes in CA, the CA mechanisms designed can be sorted as single-round (one-shot) CA and multi-round (iterative) CA. A single-round CA only processes the bidding once while an iterative CA iterates the

process of single-round combinatorial auction until some stopping conditions are satisfied. The simplified routine of single-round CA in transportation service procurement can be described as follows.

- 1) The auctioneer representing the shipper(s) provides a set of transportation requests with outsourcing prices in the auction pool.
- 2) The bidders (carriers) submit to the auctioneer their bids for a bundle of requests based on the request information to maximize their profits.
- 3) The auctioneer finds an optimal allocation of the requests to the bidders to minimize its cost, that is, to determine the winners of the bids.

And a general process of multi-round CA is illustrated in Fig. 1-1 (Kwon et al., 2005).

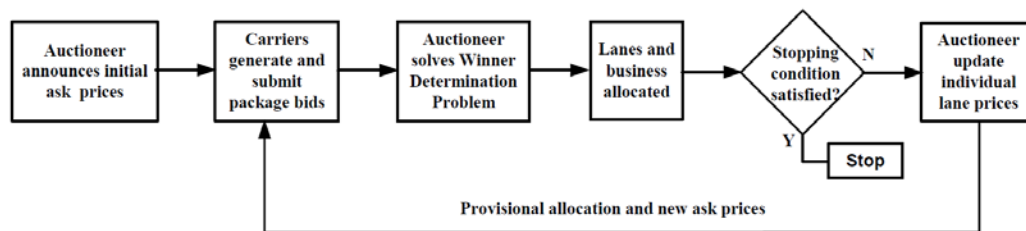


Figure 1-1 General process of multi-round combinatorial auction

Two major decision problems have to be solved in the auction process. The first one is usually referred as the bid generation problem (BGP), That is, each carrier generates its bid by selecting the requests to be included in its bundle (bid). The second one is the winner determination problem (WDP), in which the auctioneer determines the winners of the bids submitted by all bidders. Bid generation problem is usually NP-hard (Park & Rothkopf, 2005) , the same as winner determination problem (Rothkopf et al., 1998).

## 1.2 Studied problems and contributions

This thesis is devoted to investigating problems of combinatorial auctions for the procurement of truckload transportation services, from both the overall and individual perspective. From the overall perspective, the design of auction mechanism is studied with the consideration of social efficiency. And from the individual perspective, one of the major decision problems, the bid generation problem in combinatorial auctions of different context is studied for the sake of economic efficiency of single carrier. With these considerations, some issues are noticed in combinatorial auction.

Firstly, due to the decentralized nature of combinatorial auction, it is very



difficult to allocate all requests in the bidding pool at a stroke. In this context, multi-round combinatorial auction emerges to solve this problem. A multi-round combinatorial auction is that the auction process iterates multiple rounds to seek better allocation. However, without information sharing among carriers, the requests in the bundle of each carrier may be overlapping, i.e., some requests are competed by several carriers, while some other requests are not bid by any carrier. Such combinatorial auctions are often stopped with an inefficient allocation, which fail to procure services for all the requests. Even get an efficient allocation, the auction may take a large number of rounds.

Secondly, as major transportation service providers, how truckload carriers operate can influence the efficiency of the whole logistics system. In multi-round combinatorial auctions, bid generation problem of each carrier is crucial because the bids they submitted are the base of winner determination problem, and may influence the adjustment of the outsourcing prices of the requests in next round. Since all carriers are profit-driven, the requests they chose to bid for must be the ones that can bring them more profit. One request will be chosen by a carrier either it can fill up the empty vehicle reposition or the income of serving this request exceeds the cost of additional route. So, bid generation problem is usually a variant of vehicle routing problem. This problem is NP-hard and is difficult to get solution in a reasonable time for large scale problems.

Thirdly, the truckload transportation market is very competitive, which requires carriers to grasp future opportunities in transportation service. To achieve this goal, when a carrier plans its transportation operations, it must consider not only its present transportation requests but also the requests it may acquire in future. As pointed out by Wang et al. (2014) and Wang and Kopfer (2015), the assumption that only allowing the carriers to compete for the transportation requests available in the current period in an auction is rather restrictive. A more efficient auction needs to be conducted in a rolling horizon way which considers several periods (days) in its request allocation. In addition, some requests may emerge in future periods but cannot be foreseen in the current period. Whether or not to consider these future requests in the bid generation problem will have a significant impact on the efficiency of the auction over a long term.

This thesis studied three problems that aim at providing an optional solution to each of the issues mentioned above, as well as some managerial insights to the stakeholders in truckload transportation market. One of the problems focuses on

designing CA mechanisms for truckload transportation service procurement, while the other two devote to solving the bid generation problem in the process of CA.

- (1) Design of two-phase multi-round combinatorial auction mechanisms with supplementary bundles of requests offered to bid generated by the auctioneer and the carriers respectively in the second phase. Each step in the designed mechanism is formulated with mixed-integer linear programming (MILP) model. Computational experiments are conducted with randomly generated instances of different problem size as well as different proportion of number of rounds of the clock auction in the total CA rounds. Compared with single-phase clock auction, the designed two-phase mechanisms have evident advantages in time efficiency and cost savings for the auctioneer. Meanwhile, the social efficiency of the auction's outcome (request allocation) is improved by the two mechanisms.
- (2) Bid generation problem of a single carrier in the designed auction mechanism. The bid generation problem is extended to a more general case with pre-existing commitments of the carrier. Since the MILP model of this problem cannot get an optimal solution of large problem scale in reasonable time, a column generation algorithm is proposed to solve the problem appeared in the combinatorial auction. Numerical experiments of randomly generated instances demonstrate that the proposed algorithm can quickly find a near-optimal solution of the studied problem.
- (3) Bid generation problem considering multi-period and uncertainty in truckload transportation service procurement. This stochastic optimization problem is formulated as a MILP model through scenario optimization and deterministic equivalence. To solve the model, a Benders decomposition approach is proposed. Computational results with both randomly generated and realistic instances demonstrate that the Bender decomposition approach is much more efficient than CPLEX solver in terms of computation time for solving large instances of the model. The value of considering uncertain requests and multiple periods in the bid generation is also evaluated by numerical experiments.

Part of the work in this thesis has been presented in two papers. A paper related to the third problem is published in an international journal (Lyu et al., 2021) and a paper related to the first problem is published in the proceedings of an international conference (Lyu et al., 2020).

### 1.3 Organization of the thesis

This thesis is organized as follows. Chapter 1 generally introduced the research background of the thesis and briefly describe the problems studied in the thesis. The contribution of this thesis is also expounded. Chapter 2 gives a review on literatures in related fields of the studied problems from several aspects. Chapter 3 is devoted to the design of two-phase combinatorial auction mechanisms which are used to realize truckload transportation service procurement of the auctioneer from multiple carriers. Chapter 4 investigates a bid generation problem for a single carrier that participate in combinatorial auctions for truckload transportation service procurement. Chapter 5 considers a bid generation problem in truckload transportation service procurement considering multiple periods and uncertainty. Chapter 6 concludes the work of this thesis with the perspectives for future research. The outline of this thesis is illustrated in Fig. 1-2.

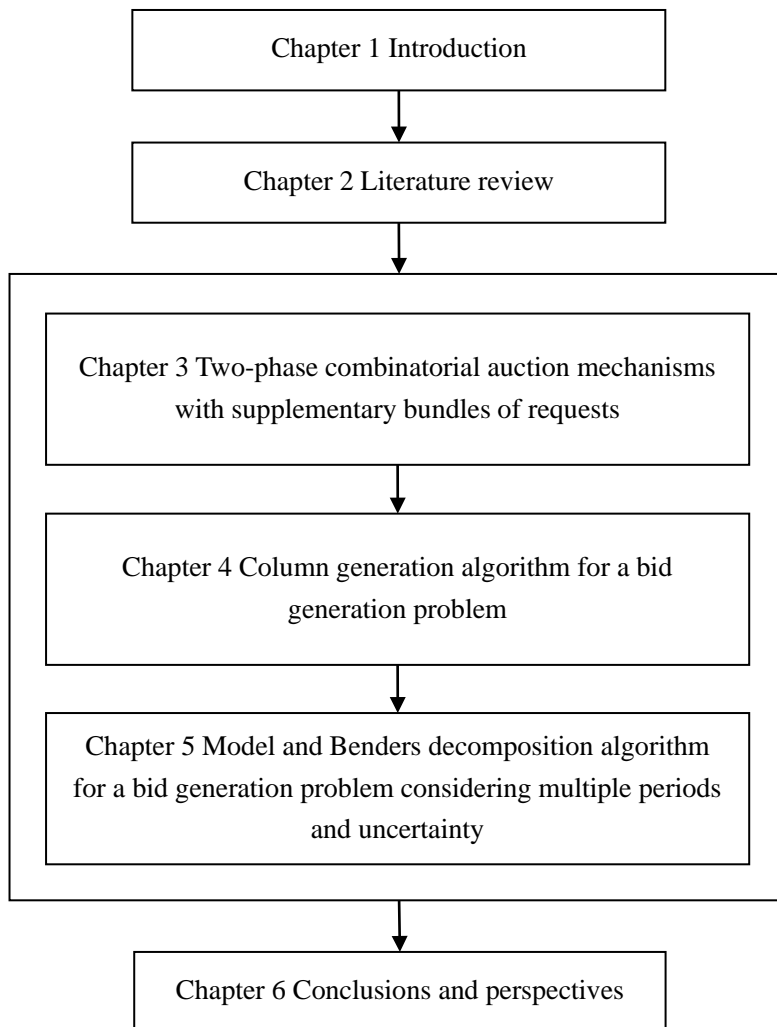


Figure 1-2 The outline of this thesis

## 2 Literature review

### 2.1 Freight transportation service procurement in electronic market

Freight transportation service procurement matches shippers' transportation requirements and carriers' capacities. In recent decades, the development of electronic commerce facilitates the development of freight transportation, online marketplaces for freight transportation service procurement emerge in numbers, such as FreightMatrix, Freight-traders and logistics.com. The electronic market makes the connection and collaboration easier among the shippers and the carriers.

Nandiraju and Regan (2003) used case studies to depict the freight transportation electronic market at that time. They classified the market mechanisms and discussed some of the key research problems for developing methodologies. Figliozzi et al. (2004a) compared the performance of electronic marketplaces with different sequential auction settings for the truckload transportation service procurement. Learning methodologies for finding good bidding strategy were also discussed. Caplice (2007) studied truckload transportation service procurement in the context of electronic market, with the consideration of marketplace formats, and how they were used. Collignon (2016) conducted exploratory and empirical analysis of electronic marketplaces for truck transportation services procurement which concern about the features, typology and performance of electronic marketplace. Lafkihi et al. (2017) also classified the mechanisms for freight transportation. Later, they gave a more complete overview of freight transportation service procurement with refined theoretical framework (Lafkihi et al., 2019). In this work, they classified the literatures of freight transportation service procurement with different criteria such as procurement mechanisms, market characteristics, procurement mechanism outcomes and research methodologies. From their literature study, the trends and gaps from the viewpoints of practitioners were identified and future prospects in freight transportation markets were also described. A review that focused on truckload transportation service procurement with statistical data was presented by Jothi Basu et al. (2015)

These works gave a macroscopical view of transportation service procurement in electronic market. Although variety of frames or mechanisms are used by different electronic marketplaces, the literatures commonly classified them into three major categories: auctions, catalogs and exchanges (negotiations), while the modes of

procurement can be long-term contract and spot market. According to the literatures, Auction-based mechanism is widely used in transportation service procurement.

## **2.2 Auction-based mechanisms for transportation service procurement**

Auction-based mechanism plays an important role in transportation service procurement, many different auction-based mechanisms can be found in former research works, for example, single-item auctions, combinatorial auctions, and double auctions. This thesis focuses on studying combinatorial auctions for truckload transportation service procurement (TSP). In this section, research works related to combinatorial auctions for transportation service procurement is reviewed with a glimpse of other auction-based mechanisms.

### **2.2.1 Combinatorial auctions for transportation service procurement**

Combinatorial auction (CA) is first proposed by Rassenti et al. (1982) for the allocation of airport landing slots. CA allows the bidders to place bids on combinations of items rather than individual items. This mechanism expressed the synergies across bundles of goods or services, which has the potential to lower the cost and increase efficiency (Lunander & Lundberg, 2013). Many works provided theoretical and practical knowledge for designing CA (Abrache et al., 2004; Bichler et al., 2009; De Vries & Vohra, 2003; Pekeč & Rothkopf, 2003). Except for transportation service procurement, CA is also adopted by many different industry environments such as robot coordination, pollution permits trade, manufacturing scheduling, school meals catering and so on (Berhault et al., 2003; Epstein et al., 2004; Kutanoglu & Wu, 1999; Leyton-Brown et al., 2000).

There are many different CA mechanism (Cramton et al., 2006), some of them are well adopted by the scholars and practitioners. The Vickrey-Clarke-Groves (VCG) mechanism (L. Ausubel & Milgrom, 2006) is a CA mechanism in which bidders report their valuations for all packages. Items are allocated efficiently to maximize the total value. Each winner pays the opportunity cost of his winnings: the incremental value is derived by assigning the bidder's items according to their next best use. The clock auction (L. Ausubel et al., 2006) is an iterative CA mechanism in which the auctioneer announces prices of the items, and the bidders indicate the quantities of each item. Prices for items with excess demand will be adjusted, then each bidder express quantities at the new prices. Progressive Adaptive User Selection

Environment (PAUSE) (Kelly & Steinberg, 2000; Land et al., 2006) is a computationally tractable CA mechanism in which the auctioneer does not face the winner determination problem. The responsibility of evaluating a combinatorial bid is transferred to the bidder who is making the bid.

The use of CA for transportation service procurement increased dramatically throughout the 1990s (Caplice & Sheffi, 2003, 2006). Sears Logistics Services seems to be the first to use CA for the procurement of transportation services. According to Ledyard et al.(2002), in 1995, Sears Logistics Services conducted a “combined-value auction” involving 854 lanes with a cost of 190 million dollars per year. Since then, CA began to be widely used on trucking service procurement. Dozens of companies adopted CA in their logistics operations to reduce transportation costs and achieve higher levels of service, such as Colgate-Palmolive Company, Ford Motor Company, Nestle S. A. and Wal-Mart Stores Inc. (Sheffi, 2004). With the considerations of incorporating service level and some other nonprice variables into the frame of CA, Sheffi (2004) drew a conclusion that CA allows both shippers and carriers to exploit the economies of scope inherent in truckload transportation. Later, Caplice and Sheffi (2006) explored CA used for truckload transportation from the perspective of shippers and carriers respectively, where the differences between TSP auctions and other auctions were examined.

Like conventional CA, the CA mechanisms designed for TSP in the works can be also sorted as single-round (one-shot) CA and multi-round (iterative) CA. It is reported that when Sears Logistics Services used combinatorial, it chose an iterative version of procurement auction with sealed bids. In this iterative auction, the bidding proceeds in multiple rounds. The iterative combinatorial auction is also referred as multi-round combinatorial auction nowadays. Compared with single-round CA, multi-round CA has two advantages. One is that multi-round CA can simplify the bid generation of bidders by providing price information of each request or each bundle of requests in each round. The other advantage is that multi-round CA provides a price-discovery process to bidders, which allows bidders to submit more relevant bids to maximize the social efficiency of the auction.

Some scholars believe that research for CA mainly focused on multi-round CA, while single-round CA are commonly used in practice (An et al., 2005). But in transportation service procurement, it seems that both single-round and multi-round CA drew the attention of researchers.

### 2.2.1.1 Single-round CA mechanisms for TSP

Song and Regan (2003) examined the benefits of CA for transportation service procurement from the perspective of carriers. Optimal bidding strategy was discussed with optimal operating cost calculated. Based on a simple simulation model, they examined the impact of CA with inherent and difficult subproblems. Although they only studied the case with the number of requests on each lane limited to one, the results can still demonstrate potential benefits of CA for the procurement of transportation services.

Based on their teaching case study, Elmaghraby and Keskinocak (2000; 2004) presented an overview of combinatorial auctions and the experience of Home Depot in using a single-round CA mechanism for outsourcing truckload transportation capacity. In the case studied, carriers enjoyed much more freedom under the traditional auction settings of Home Depot. Carriers were allowed to submit bids with one or multiple lanes. In addition, they were able to specify additional restrictions on their aggregate bids. They reported that this was a successful implementation of the CA for transportation service procurement.

Srivastava et al. (2008) investigated CA used in the procurement of global transportation services. A single-round CA mechanism was designed with bid generation and evaluation. Although the numerical experiments showed that the single-round CA mechanism performed well, the authors pointed out that multi-round auctions for the proposed procurement would have many advantages to be explored in the future.

Chen et al. (2009) developed models of CA for truckload service procurement in a single round as well as presented an implicit bidding approach that enables the complete set of all possible bids are considered. The tractability of the proposed approach was proved by numerical experiments.

### 2.2.1.2 Multi-round CA mechanisms for TSP

Kwon et al. (2005) considered an integrated multi-round CA mechanism for truckload transportation service procurement. In this mechanism, the shippers allowed bids with a bundle of requests and solve the winner determination problem to assign the requests to the carriers. The carriers, on the other hand, generate bids by employing optimization models to discover profitable lanes in each round. Price information was adjusted according to the result of the winner determination problem which influence the bidding decision of the carriers for the next round. In the designed framework of CA, the item prices were constructed to be used as

coefficients in bidder optimization problems rather than bundle prices. Numerical results illustrated that the CA mechanism proposed in this work benefited both shippers and carriers. An elaboration and extension of this work can be found in Ma (2008), in which a bid generation problem for carrier and a stochastic winner determination problem with shipment volume uncertainty in CA were also discussed.

Day and Raghavan (2008) described a multi-round combinatorial procurement auction format which incorporated features from the PAUSE auction of Kelly and Steinberg (2000) and the clock-proxy auction of Ausubel et al. (2006). Bundle synergy information was provided for all interactive phases in the CA. The revelation of price information on individual items was emphasized in order to reduce the number of bundles. The tractable winner determination problem makes this auction format well-suited to large combinatorial auctions.

Tian et al. (2011) discussed a practical transportation service procurement problem originated from an external project. Their work devoted to developing a CA strategy to help the department of transportation purchasing at Royal Philips to determine the annual transportation service procurement cost. The problem was formulated into a linear integer programming model and proved to be NP-hard. So, iterative rounding heuristic algorithm was proposed which achieved good-quality solutions.

Wang and Wang (2015) proposed an applicable mechanism of two-round CA with bundling optimization in freight transportation service procurements. In this mechanism, after a first-round auction, the auctioneer integrates the requests into several bundles based on former bidding results obtained from the winner determination problem. Then, the carriers bid for the bundles proposed by the auctioneer in the second round of auction. The bundling optimization problem by the auctioneer was described as a multi-objective model with two criteria on price complementation and combination consistency. A quantum evolutionary algorithm was developed as well as compared with a contrast genetic algorithm. Computational results demonstrated that the algorithm they proposed performed better for small and middle size problems.

### **2.2.2 Other common auction-based mechanisms**

Varies of auction-based mechanisms were designed and used for transportation service procurement. Here, some common types of auction-based mechanisms with representative research works are briefly presented.



### 1) Double auction mechanisms

For TSP, a double auction is a process of buying and selling transportation services with multiple shippers and multiple carriers. The double auction mechanism allows bilateral bidding between the shippers and the carriers, i.e., the carriers submit their bids and shippers submit their asking prices. The market is then cleared by a third-party auctioneer with proper prices for the bids. This mechanism is studied by some researchers to reduce transportation cost, improve allocation efficiency, and pursue social welfare (Garrido, 2007; Huang & Xu, 2013; Xu & Huang, 2013; Xu et al., 2017; L. Zhou & Xu, 2017).

### 2) Sequential auction mechanisms

Generally, a sequential auction is an auction in which several items are sold, one after the other, to the same group of potential buyers. In TSP, the auction reverses that the carriers compete for the requests of the shippers. So this framework is usually chosen to model and study carrier competition in TSP. Representative researches of TSP using sequential auctions are presented by Figliozzi et al (2004b, 2005, 2006) Mes (2008) and Budde (2014).

### 3) Auction-based exchange mechanisms

Auction-based exchange mechanisms are usually used for carrier collaboration to help them survive in the fiercely competitive transportation market. This kind of mechanism benefits carrier by reducing empty vehicle repositions and increasing vehicle fill rates. In this mechanism, the carriers can be either a seller or a buyer of transportation services. The exchange mechanism is subdivided into four phases: initialization phase, outsourcing phase, insourcing phase, and final evaluation phase (Dai & Chen, 2011). With growing interest in carrier collaboration from industrial practitioners and academic researchers, more and more works spring up that studying this kind of mechanism, for example, Schiwind et al. (2009), Berger and Bierwirth (2010), Li et al. (2015) and Chen (2016).

## **2.3 Bid generation problems in transportation service procurement**

Bid generation problem (BGP) is a key decision problem in CA, which is usually solved by the carriers. This problem focuses on request selecting and bundling to submit in CA. BGP is also recognize as bid construction problem, bundle generation problem or request bundling problem. Many research works have contributed to this problem in CA for the procurement of transportation services. Based on whether there are stochastic factors when solving the problem, a BGP can be either deterministic or

stochastic.

### **2.3.1 Deterministic bid generation problems**

#### 2.3.1.1 Single period bid generation problems

Song and Regan (2005) examined some computationally tractable approximation methods for BGP in CA for acquiring transportation contracts which discuss bid valuation and construction in two contexts: in the absence or presence of pre-existing commitments. The method they developed provides a way for carriers to discover their true costs and construct profitable bids.

Wang and Xia (2005) study a carrier's BGP in the context of truckload TSP. The problem focused on the bundling method when an OR bidding language (Nisan, 2000) is used. They defined the optimality criterion for the carriers of combinatorial bids. Two heuristics are developed and compared based on the fleet assignment model and the nearest insertion method respectively.

Lee et al. (2007) considered the carrier's optimal BGP in CA for transportation procurement in truckload transportation. In this work, the carriers employ vehicle routing models to identify sets of lanes to bid for based on the actual routes. An optimization model that integrates the generation of bids and the selection of routes was proposed to maximize the profit of the carrier. Both column generation and Lagrangian relaxation-based techniques were employed to solve the model.

Chang (2009) investigated the bidding problem of single-round CA to provide decision supports for truckload carriers. The bid generation and evaluation problems in CA were formulated as a synergetic minimum cost flow problem in which the average synergy values between loads were estimated. A column generation approach was proposed to solve the specific problem. The author believed that a truckload carrier can easily determine the desirable bid packages without evaluating all possible bundles of loads through adopting the proposed advisor.

Buer (2014) proposed an exact and two heuristic strategies for bidding on subsets of requests to support a carrier in CA. The exact bidding strategy is based on the concept of elementary request combinations. The author shows that it is sufficient for a carrier to bid on each elementary request combination in order to guarantee the same result as bidding on each element of the powerset of the set of tendered requests. The two heuristic bidding strategies identify promising request combinations, where pairwise synergies based on saving values as well as the capacitated  $p$ -median problem were used. The proposed heuristic bidding strategies can help a carrier to increase its chance to win as well as reduce the computational burden to participate in

a combinatorial auction for TSP. Computational results showed that the heuristics had great advantage over exact strategy in achieving available sales.

Yan et al. (2018) investigated a BGP for transportation service procurement from a less-than-truckload perspective in which the carriers generate bids using a bundled price to maximize their utility. Mixed integer programming models were developed from both the carriers' and the shippers' perspectives to establish a relationship between the quoted price and the likelihood of winning. This helps assist the carriers in balancing the potential benefits and the possibility of winning the bid. An intelligent algorithm based on Particle Swarm Optimization was designed to solve the proposed model.

Gansterer and Hartl (2018) studied a centralized BGP in carrier collaboration aiming at providing a reduced set of offered bundles that maximizes the total coalition profit. But the bundles in this problem were generated to bid by the carriers in the auction, not submitted as a bid of carrier.

#### 2.3.1.2 Multi-period bid generation problems

Mamaghani et al. (2019a) firstly considered a multi-period BGP of a carrier in the context of carrier collaboration. In this problem, the carrier needs to determine which requests to bid and in which period to serve them to maximize its total profit. A mixed-integer linear programming model was formulated, and a genetic algorithm combined with simulated annealing was proposed to solve the problem.

Later, they studied a BGP which is the extension of the former problem (E. Mamaghani et al., 2019b). In this problem, the carrier wants to determine within a time horizon of multi periods which requests to bid and serve and its multi-period routing plan to maximize its profit and minimize delivery lead times. An Improved Tabu Search algorithm was proposed to solve the problem.

The study on multi-period BGP or CA for TSP is rare. But there are some other works related to multi-period auctions. For example, Brunekreeft (2001) investigated the multi-period CA in electricity spot market, Arroyo and Conejo (2002) studied multi-period auction for a pool-based electricity market, and Lau et al. (2007) proposed a multi-period CA mechanism for distributed resource allocation and scheduling.

#### 2.3.2 Stochastic bid generation problems

Triki et al. (2014) dealt with the generation of bundles of requests in the context of long-haul truckload transportation services, where a probabilistic optimization

model, which considers together the BGP, the pricing problem and the routing problem of a carrier, was proposed. Two heuristics were developed to solve the model.

Kyuzu et al. (2015) studied simultaneous transportation procurement auctions from a truckload carrier's perspective. A stochastic bid price optimization problem was formulated to maximize a carrier's expected profit. The formulation took consideration of the synergies among the lanes and the bidding patterns of the carriers. An iterative coordinate search algorithm was developed for solving the problem.

Hammami et al. (2020; 2021) considered BGP with stochastic clearing prices to maximize the expected net profit of the carriers. The problem took uncertainty on other competing carriers' offers into account. Selection and pricing decisions were integrated to generate multiple combinatorial bids. An exact non-enumerative method and a hybrid heuristic were proposed to solve the problem.

## **2.4 Route planning for truckload transportation**

In combinatorial auctions for TSP, a carrier's bid generation problem usually needs to consider the synergies among the new acquired requests and the pre-existing requests to decrease empty vehicle repositioning and to increase profits. So, the bid generation problems for TSP are usually considered with route planning.

The freight transportation mode studied in this thesis is truckload (TL) transportation. Truckload transportation is nonstop, i.e., when a vehicle serves a truckload request, it travels directly from its origin to destination without visiting any other terminal. The basic unit of a truckload request is usually called a lane. Many researchers have devoted to the study of route planning for TL transportation.

### **2.4.1 Vehicle routing problem with full truckload**

The vehicle routing problem (VRP) with full truckload is a variant of classical VRP in which the vehicles serve directed arcs (lanes) not nodes in the graph. It can also be recognized as an arc routing problem or a one-to-one pickup and delivery problem.

VRP with truckload was firstly tackled by Ball et al. (1983). The problem determined an optimal fleet size and the resulting vehicle routes while satisfying maximum route-time restrictions. The problem was formulated, some approximate solution strategies were also described for solving the problem. Desrosiers et al. (1988) considered a VRP with full loads and time limit constraints. They formulated the problem as an asymmetrical travelling salesman problem with two types of

restrictions, which are distance and time restrictions. Arunapuram et al. (2003) developed a branch-and-bound algorithm for solving an integer-programming formulation of VRP with full truckloads which took into consideration the time-window constraints and waiting costs. Gronalt et al. (2003) dealt with the pickup and delivery of full truckloads under time window constraints with the objective to minimize empty vehicle movements. An exact formulation of the problem is provided for the problem, different saving-based heuristics were also proposed. Li and Lu (2014) studied a full truckload VRP with profits. In this problem, more than one delivery points are corresponded to the same pickup point, and there may be multi tasks on the same lane. A hybrid genetic algorithm is proposed for the problem. Bouyahyious and Bellabdaoui (2017) proposed an ant colony optimization to solve a full-truckload selective multi-depot vehicle routing problem under time windows constraints to maximize the total profit. Faiz et al. (2019) considered a variant of a truckload open vehicle routing problem with time windows and presented two integer linear programming models to formulate the problem, the second one was solved by designing a column generation framework. Xue et al. (2021) studied a multi-shift full truckload vehicle routing problem and proposed a hybrid pricing and cutting approach for it.

#### **2.4.2 Lane covering problem**

With the development of collaborative transportation, lane covering problem (LCP) arises and are draws the attention of many scholars. The lane covering problem aims at finding a set of tours that cover all lanes representing TL transportation requests with minimum transportation cost. This is problem is usually formulated with the consideration of flow equilibrium of the vehicles.

LCP for shipper collaboration was formulated by Ergun et al. (2003; 2007a; 2007b) and several algorithms were proposed to solve the problem, for example, linear-time algorithm and greedy algorithm. They also proved that both the cardinality constrained lane covering problem and the length constrained lane covering problem are NP-hard. LCP with time windows was considered by Ghiani et al. (2008). A heuristic approach based on Lagrangian relaxation was proposed for the solution of the problem. A multicarrier LCP under carrier collaboration was introduced and analyzed by Özener et al (2011), where lane exchange mechanisms were also investigated. Xu et al. (2017) studied a simplified LCP appeared in carrier collaboration realized by a bundle double auction. LCP with partner bounds in truckload transportation was investigated by Kuyzu et al. (2017). A set partitioning

type integer program was formulated. Column generation and branch-and-price approaches were developed for the problem. All of these works adopted LCP or its variants as a mathematical formulation.

### **2.4.3 Rolling horizon planning**

Rolling horizon planning is virtually not a routing problem but a planning mechanism that considers multi-period. When considering the bid generation and routing problem in a rolling horizon, the carrier acquires requests during the entire time horizon rather than in the current decision period. Each request in the transportation market may have a service window composed of several consecutive periods, and the request can be served in any period within its window. In each period, plans for next few periods are made, which will be adjusted according to the dynamic information in the market.

Zhou et al. (2006a; 2006b) studied a generic real-time truckload pickup and delivery problems. A mixed integer programming formulation for the problem, three rolling horizon strategies for the problem were also considered. A dynamic truckload pickup and delivery problem with time windows was investigated by Zhou (2013) with a rolling horizon framework for the dynamic assignment and sequencing of trucks. Rolling horizon planning for a dynamic collaborative routing problem with full-truckload pickup and delivery requests were considered by Wang and Kopfer. (2013; 2015). And Wang et al. (2014) studied an auction with rolling horizon for urban consolidation center, which addressed the challenge that shippers/carriers plan their deliveries many periods ahead.

## **2.5 Summary of the literature review**

This thesis studies auction mechanism and bid generation in the procurement of truckload transportation services. In this chapter, works related to market of transportation service procurement, the auction-base mechanism for the procurement of transportation services, the bid generation and routing problems are reviewed. For the reviews of market of transportation service procurement, the corresponding research works are sorted by methods to solve the problem. For the auction-base mechanism for the procurement of transportation services, the different mechanisms are studied and evaluated. Both single round and multi-round auction mechanisms are considered. For the bid generation problem, multiple methods are developed for solving it. Both deterministic and stochastic variants of this problem are studied.

There are some findings from the literature review.

Firstly, freight transportation electronic marketplaces flourish with the prosperity of electronic commers. Auction-based mechanism are mostly used for transportation service procurement. Among different mechanisms, combinatorial auction is well adopted by both academic scholars and industrial practitioners. Different combinatorial auction mechanisms were designed with specific context and constraints. The major challenge in CA mechanism design is to ensure both the time and solution efficiency, which will be concerned by researchers for a long time in the future.

Secondly, bid generation problem as a major decision problem in CA for TSP have drawn many researchers' attention, different bundling and pricing strategies were designed. However, most studies focused on deterministic BGP while the studies of stochastic BGP only involved stochastic prices for the requests. Thirdly, generally, vehicle routing problems are considered in BGP for bundling the requests/lanes. The BGP intractable for large scale problems due to its computational complexity. Efficient algorithms need to be designed for large scale problems.

Finally, a planning strategy with rolling horizons came into public view since it is closer to practical application and provides more choices for the carriers to achieve better operations, but BGP with both stochastic and dynamic factor has not been considered yet. The work of this thesis is carried out based on these findings.

## 3 Two-phase combinatorial auction mechanisms with supplementary bundles of requests

### 3.1 Introduction

In logistics business, shippers who may be manufacturers or distributors procure transportation services from carriers. The competitive market with fragmented shippers and carriers makes a perfect circumstance to use combinatorial auction (CA) in transportation service procurement (TSP). CA can help shippers reduce their logistics costs for procuring the transportation services.

For the procurement of transportation services, an ideal situation is that all the transportation requests of a shipper that need to be served are allocated to the carriers, and each request is allocated to a single carrier. This allocation can be realized by a centralized approach which is based on a centralized mathematical programming model, or a decentralized approach, such as a combinatorial auction. The centralized approach can solve the allocation problem at one stroke. However, confidential information of the carriers such as pre-existing contracts and request serving costs need to be revealed, which is not practically appealing. CA on the other hand, does not need to reveal any confidential information of the carriers and thus becomes very popular now. The mechanism of CA can have a direct influence on its efficiency, both in time and request allocation.

This chapter studies a problem raised in truckload transportation service procurement which involves one or multiple shippers and multiple carriers. Both centralized and decentralized approaches are investigated in this chapter. On the one hand, a mixed-integer linear programming model is formulated for the TSP problem solved by using a centralized approach. On the other hand, motivated by the clock-proxy auction proposed by Ausubel et al. (2006), two two-phase multi-round CA mechanisms are proposed to solve the same problem.

The clock-proxy auction combines the simple and transparent price discovery of the clock auction with the efficiency of the proxy auction. As in the clock-proxy auction, the second phase in the proposed CA mechanisms is also used to improve the efficiency of request allocation. The objective is to find an effective bundling strategy for the second phase of CA, which can accelerate the process of the CA with improved results. In the proposed two-phase CA mechanisms, the first phase is clock



auction, in which the auctioneer increases the price of a request (lane) if no carrier bids for this request. Each carrier generates its bid based on the prices of all requests open for bid in each round. The second phase mainly aims at selling the leftover requests (lanes) after the first phase by generating supplementary bundles of requests open for bid. The two CA mechanisms generate supplementary bundles by the auctioneer and the carriers respectively. In case the auctioneer generates the supplementary bundles, each carrier decides if it bids for one or multiple supplementary bundles. In case the carriers generate supplementary bids, each carrier generates and bids for bundles of requests based on the results of the last round of the CA. The prices for serving the supplementary bundles may also be adjusted during the second phase. To our best knowledge, this is a new variant of CA for TL transportation service procurement.

The rest of this chapter is organized as follows: In Section 3.2, the studied problem is described and formulated with a centralized mathematical programming model. Section 3.3 presents in detail the proposed two two-phase CA mechanisms respectively. The results of computational experiments evaluating the mechanisms are reported in Section 3.4. Section 3.5 concludes this chapter with perspectives for future research.

## **3.2 Problem description and centralized mathematical programming model**

In the considered TSP problem, one or multiple shippers have a set of truckload transportation requests to outsource to a set of carriers. Each truckload request is represented by a lane with an origin and a destination in a transportation network. Each carrier involved in the TSP has a fleet of vehicles initially located at its own vehicle depot. Each vehicle must leave and return to its own depot before and after serving the lanes that are assigned to it. The travel duration of each vehicle is limited, and a fixed cost is incurred if a vehicle serves a tour. The revenue for serving each lane is given, which is independent of the profit/cost allocation between the shippers and the carriers involved.

The problem is considered from the perspective of social efficiency. The objective is to minimize the total travel distance/cost of vehicles/carriers for serving all requests (lanes), which refers to the consumption of fuel or the air pollution of all routes to serve the requests. That is to say, the maximization of the social efficiency is equivalent to the minimization of the total transportation cost for serving all lanes.

When formulating the problem, the for-bid lanes contain all lanes that the shippers want to outsource to the carriers. If a carrier wants to acquire one or more for-bid lanes, except for selecting the lanes to bid, it must also construct its vehicle routes to serve these lanes. Each vehicle of a carrier serves a single tour with requests. The problem is a multi-depot (multi-carrier) truckload vehicle routing problem with fixed costs and maximum duration constraint.

For the convenience of the formulation, the following notations are firstly introduced:

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**Indices and sets**

$N$ : set of all nodes in the transportation network considered

$A$ : set of all possible lanes

$K$ : set of carriers

$d_k (d'_k)$ : depot of carrier  $k$ ,  $k \in K$

$H_k$ : set of vehicles of carrier  $k$ ,  $k \in K$

$L_b$ : set of for-bid lanes,  $L_b \subseteq A$

**Parameters:**

$c_{i,j}^k$ : travel cost of lane  $(i, j)$  of carrier  $k$ ,  $(i, j) \in A$ ,  $k \in K$

$t_{i,j}^k$ : travel time of lane  $(i, j)$  of carrier  $k$ ,  $(i, j) \in A$ ,  $k \in K$

$B$ : maximum travel duration of each vehicle

$f_k$ : the fixed cost of each vehicle of carrier  $k$ ,  $k \in K$

**Decision variables:**

$$v_{i,j}^{k,h} = \begin{cases} 1, & \text{if for-bid lane } (i, j) \text{ is served by carrier } k \text{ with its vehicle } h, \\ 0, & \text{otherwise} \end{cases} \quad (i, j) \in L_b, h \in H_k, k \in K$$

$$x_{i,j}^{k,h} = \begin{cases} 1, & \text{if vehicle } h \text{ of carrier } k \text{ travels through arc } (i, j), \\ 0, & \text{otherwise} \end{cases} \quad (i, j) \in A, k \in K, h \in H_k$$

$S_i^{k,h}$ : the time at which vehicle  $h$  of carrier  $k$  leaves node  $i$ ,  $i \in N$ ,  $k \in K$ ,  $h \in H_k$

---

Note that to simplify the formulation, here adopted an assumption that for any for-bid lane with a pair of origin and destination, there is at most one request. For example, if there is a for-bid lane  $(i, j)$ , there is no other for-bid lane with the same origin and destination in the bidding pool. The model and mechanisms proposed for

this problem can be easily extended to the case without such an assumption. This can be done by transforming the underlying transportation network in the following way: for each pair of origin node and destination node, if there are multiple lanes (say  $m > 1$  lanes) of the same type from the origin node to the destination node, one can create  $m$  copies of the two nodes (including original ones) with zero distance between any two copies of the origin node or the destination node such that only a single lane of this type exists from the  $i$ -th copy of the origin node to the  $i$ -th copy of the destination node ( $1 \leq i \leq m$ ).

Then the centralized model can be formulated as:

Model *CP*

$$\text{Min} \sum_{k \in K} \sum_{h \in H_k} \left( \sum_{(i,j) \in A} c_{i,j}^k x_{i,j}^{k,h} + \sum_{i \in N} f_k x_{d_k,i}^{k,h} \right)$$

s.t.

$$\sum_{j \in N} x_{i,j}^{k,h} = \sum_{j \in N} x_{j,i}^{k,h}, \quad i \in N \setminus \{d_k, d'_k\}, \quad k \in K, \quad h \in H_k \quad (3-1)$$

$$\sum_{j \in N} x_{i,j}^{k,h} \leq 1, \quad i \in N, \quad k \in K, \quad h \in H_k \quad (3-2)$$

$$\sum_{i \in N \setminus d_k} x_{d_k,i}^{k,h} = 1, \quad k \in K, \quad h \in H_k \quad (3-3)$$

$$\sum_{j \in N \setminus d'_k} x_{j,d'_k}^{k,h} = 1, \quad k \in K, \quad h \in H_k \quad (3-4)$$

$$x_{i,j}^{k,h} \geq v_{i,j}^{k,h}, \quad (i,j) \in A, \quad k \in K, \quad h \in H_k \quad (3-5)$$

$$\sum_{k \in K} \sum_{h \in H_k} v_{i,j}^{k,h} = 1, \quad (i,j) \in L_b \quad (3-6)$$

$$\sum_{(i,j) \in A} x_{i,j}^{k,h} t_{i,j}^k \leq B, \quad k \in K, \quad h \in H_k \quad (3-7)$$

$$S_{d_k}^{k,h} = 0, \quad k \in K, \quad h \in H_k \quad (3-8)$$

$$S_j^{k,h} \geq S_i^{k,h} + x_{i,j}^{k,h} t_{i,j}^k - B(1 - x_{i,j}^{k,h}), \quad i, j \in N, \quad k \in K, \quad h \in H_k \quad (3-9)$$

$$v_{i,j}^{k,h} = 0, \quad (i,j) \in A \setminus L_b, \quad h \in H_k, \quad k \in K \quad (3-10)$$

The objective function in this model is to minimize the total cost of all carriers, which is composed of two types of costs, the travel costs and the fixed costs. Constraint (3-1) ensures the vehicle flow equilibrium at each node except the depots of the carriers because each depot node is duplicated as two nodes, which are the

origin node and the destination node of the depot respectively. Constraint (3-2) indicates that for any vehicle, if it leaves a node, the next node it can visit is unique. Constraints (3-3) and (3-4) guarantee that each vehicle leaves its corresponding depot to start its service and return to the same depot after completing the service. Constraint (3-5) ensures that all lanes with a transportation task will be served. Constraint (3-6) guarantees that each for-bid lane is served at most once by a vehicle of some carrier. Constraint (3-7) ensures a maximum travel duration for each vehicle. The departure time of each vehicle from its depot is set to 0 in constraint (3-8). Constraint (3-9) ensures that if a vehicle travels through lane  $(i, j)$ , the time difference between the departure time at node  $j$  and that at node  $i$  is at least the travel time. In real life, there may be a loading time at a pickup node and an unloading time at a delivery node, if necessary, it is easy to add the two service times to the model. Constraint (3-9) can help to eliminate all subtours in each route. Constraint (3-10) defines the value of each binary variable  $v_{i,j}^{k,h}$  according to whether it is related to a for-bid lane. If it is not related, the value of this binary variable is set to 0.

Except for the minimization of the total cost of all carriers, an optimal solution of the model also provides an efficient allocation of the for-bid lanes among carriers, as well as the vehicle routes for each carrier.

### 3.3 Combinatorial clock auction

Combinatorial auction is an auction mechanism which allows bidders to bid for several items each time. As introduced in Chapter 1 and 2, based on whether the auction process iterations, combinatorial auction mechanisms can be classified into single-round combinatorial auction and multi-round combinatorial auction. The general process of multi-round combinatorial auction has been well presented in Chapter 1, Fig. 1-1.

Combinatorial clock auction (CCA) is a representative auction mechanism for multi-round combinatorial auction. It is an iterative auction procedure in which the auctioneer announces the price for each item to be sold. Then each bidder indicates the quantity of each item it wants to buy at the current price. The price of each item with excess demand will increase in the next iteration (round), and then the bidders express their buying quantities at the new prices. This process is repeated until there is no item with excess demand. It provides a simple and effective way to discover the values (prices) of the items.

When applying combinatorial clock auction to transportation service

procurement, without information sharing among carriers, the requests bid by carriers in the clock auction may be overlapping even if the prices of the requests have been raised sufficiently high. We often observe the situation where some requests are competed by several carriers, while some other requests are not bid by any carrier. In this case, the combinatorial clock auction is often stopped without an efficient allocation of requests, which prevents the auctioneer (shipper) from procuring transportation services for some requests. Even the combinatorial clock auction can obtain an efficient allocation finally, it may take a large number of rounds to achieve it. To avoid such situations, more effective auctions mechanisms need to be designed for finding an efficient allocation with higher efficiency.

Combinatorial clock-proxy auction is proposed by Ausubel et al. (2006). This auction with two phases combines a clock phase, during which prices rise and bidders state their demands in response to the current prices, with a final round in which bidders submit sealed package bids. The final round is seen as the second phase and supplementary to the clock rounds. It pushes the outcome of the auction toward an efficient allocation with competitive payoffs for the bidders and a competitive revenue for the seller. In the clock-proxy auction, all bids are kept live throughout the auction process. There are no bid withdrawals. To learn more about this auction, one can refer to Levin and Skrzypacz (2016), Ausubel and Baranov (2017a, 2017b), and Janssen and Kasberger (2019).

Although previous studies on combinatorial clock-proxy auction show that adding another phase after the clock auction can improve the social efficiency of its outcome, no problem-specific method has been proposed to help the bidders generate supplementary bids in the second phase. Motivated by this, in this chapter, two-phase auction mechanisms with clock auction and supplementary bidding phase are examined, and two methods for generating supplementary bids in the second phase are proposed.

### **3.4 Two-phase auction mechanisms with supplementary bids**

In this section, two-phase CA mechanisms for truckload transportation service procurement are proposed. The first phase is a clock auction, hereafter named the clock auction phase. It is an iterative procedure. In each iteration (round), the auctioneer updates the prices of the lanes open for bid and each carrier generates a bid based on the prices and submits it to the auctioneer. The second phase aims at improving the efficiency of the final allocation of the for-bid lanes to the carriers by

providing some supplementary bids, hereafter named the supplementary bidding phase. In this phase, some supplementary bundles of requests open for bid are provided based on the tentative winning bids. The two mechanisms are proposed from the perspective of the auctioneer and the carriers respectively. That is, one mechanism provides supplementary bids generated by the auctioneer, and another mechanism generates supplementary bids by the carriers. During the whole process of the CA, all submitted bids will be kept alive, and a winning bid can come from any conducted round. In the following, the two-phase mechanisms are presented in detail.

### 3.4.1 The clock auction phase

In the clock auction phase, the auctioneer announces all lanes open for bid and the initial prices of the for-bid lanes before the auction begins. The information about each for-bid lane includes its pick-up (origin) point and delivery (destination) point. There are two steps in each round of the clock auction phase. The first step is that each carrier solves a bid generation problem (BGP) and submits the generated bid to the auctioneer. In this BGP, the carrier considers the lanes selected to serve and the vehicle routes to serve them. The second step is that the auctioneer solves a winner determination problem (WDP) and announces tentative winning bids in this round.

In each round of this phase, after the first step, the auctioneer collects the bids submitted by all carriers and solves a WDP considering all submitted bids to determine tentative winning bids in the second step. The auctioneer then adjusts the prices of the lanes. For those lanes which are overlapped, the prices will be decreased according to the number of competitors, and for those lanes which are not contained in any of the bids in the current round, the prices will be increased. The rule used to update these prices is to decrease or increase them with a fixed value or a given percentage. In the next round, the carriers repeat the first step based on the new prices and the auctioneer repeats the second step considering newly collected bids in this round. This iterative process will be terminated when a stopping condition is satisfied. The BGP and WDP in the two steps are presented below.

#### ***Step 1:*** BGP of each carrier

In each round of the clock auction phase, each carrier has to solve a bid generation problem to select the for-bid lanes it wants to serve and the vehicle routes to serve them. The selected lanes will then be packed as a bundle, which is the bid to submit to the auctioneer in this round. In each round, the BGP is solved based on the latest prices of all for-bid lanes. The BGP can be formulated as follows where  $P_{i,j}$

denotes the serving price of the for-bid lanes:

Model *BGP*

$$\text{Max} \sum_{h \in H} \left( \sum_{(i,j) \in L_b} v_{i,j}^h P_{i,j} - \sum_{(i,j) \in A} c_{i,j} x_{i,j}^h - \sum_{i \in N} f x_{d,i}^h \right)$$

s.t.

$$\sum_{j \in N} x_{i,j}^h = \sum_{j \in N} x_{j,i}^h, \quad i \in N \setminus \{d, d'\}, \quad h \in H \quad (3-11)$$

$$\sum_{j \in N} x_{i,j}^h \leq 1, \quad i \in N, \quad h \in H \quad (3-12)$$

$$\sum_{i \in N \setminus d} x_{d,i}^h = 1, \quad h \in H \quad (3-13)$$

$$\sum_{j \in N \setminus d'} x_{j,d'}^h = 1, \quad h \in H \quad (3-14)$$

$$x_{i,j}^h \geq v_{i,j}^h, \quad (i,j) \in A, \quad h \in H \quad (3-15)$$

$$\sum_{h \in H} v_{i,j}^h \leq 1, \quad (i,j) \in L_b \quad (3-16)$$

$$\sum_{(i,j) \in A} x_{i,j}^h t_{i,j} \leq B, \quad h \in H \quad (3-17)$$

$$S_d^h = 0, \quad h \in H \quad (3-18)$$

$$S_j^h \geq S_i^h + x_{i,j}^h t_{i,j} - B(1 - x_{i,j}^h), \quad i, j \in N, \quad h \in H \quad (3-19)$$

$$v_{i,j}^h = 0, \quad (i,j) \in A \setminus L_b, \quad h \in H \quad (3-20)$$

The objective function is to maximize the net profit of the carrier since they participate in the CA for TSP for profit. The constraints in this model are almost the same as in model *CP* except for the index  $k$  which represents a carrier is removed from all constraints because this model is for a single carrier. Note that in model *CP*, constraint (3-6) is an equality, but in this model, constraint (3-16) is an inequality constraint. This is because model *CP* aims at allocating all for-bid lanes among the carriers, but this BGP helps the carrier determine whether to bid for a for-bid lane or not.

**Step 2:** WDP of the auctioneer

In each round of the clock auction phase, after collecting all bids in this round, the auctioneer has to solve a winner determination problem to determine tentative

winning bids. To formulate the WDP, the following notations are introduced first:

---

**Indices and sets:**

$M$ : the number of rounds so far in the clock auction

$R_k^m$ : the bid generated by carrier  $k$  in round  $m$ ,  $k \in K$ ,  $m \in M$

**Parameters:**

$P_r$ : the out-sourcing price of bid  $r$ ,  $r \in \bigcup_{m \in M} \bigcup_{k \in K} R_k^m$

$Q_l$ : the revenue of carrying out request (lane)  $l$ ,  $l \in L_b$

$a_l^r = \begin{cases} 1, & \text{if lane } l \text{ is in bid } r, l \in L_b, r \in \bigcup_{m \in M} \bigcup_{k \in K} R_k^m \\ 0, & \text{otherwise} \end{cases}$

**Decision variables:**

$w_r = \begin{cases} 1, & \text{if bid } r \text{ wins} \\ 0, & \text{otherwise} \end{cases}, r \in R$

$z_l = \begin{cases} 1, & \text{if lane } l \text{ is not contained by a winning bid} \\ 0, & \text{otherwise} \end{cases}; l \in L_b$

---

Here, the parameter  $P_r$  is determined by the prices of the for-bid lanes announced by the auctioneer in the corresponding round of the clock auction. The out-sourcing price of a bid  $r$  is the sum of the out-sourcing prices of all the for-bid lane included. The parameter  $Q_l$  is given in advance which is independent of the auction. It can be viewed as the revenue that a shipper can obtain by serving request (lane)  $r$  by any carrier. If no carrier serves this lane, the shipper will not obtain this revenue, this loss can be considered a cost for the shipper. Then the WDP can be formulated as:

Model WDP

$$\text{Min} \sum_{r \in R} P_r w_r + \sum_{l \in L_b} Q_l z_l$$

s.t.

$$\sum_{r \in R} a_{l,r} w_r + z_l = 1, l \in L_b \quad (3-21)$$

$$\sum_{r \in \bigcup_{m \in M} R_k^m} w_r \leq 1, k \in K \quad (3-22)$$



This model is to minimize the total cost of the shippers represented by the auctioneer. The cost is composed by two parts. One is the out-sourcing cost paid to the carriers by the shipper(s). Another is the loss of the requests unserved. This objective encourages the auctioneer to procure truckload services as many as possible with a minimum cost. Constraint (3-21) ensures that there is no overlapping of requests (lanes) among the winning bids, that is, any for-bid lane can only be served by a unique carrier. Constraint (3-22) guarantees that for each carrier, at most one bid it submits can win. That is because during the iterative process of the clock auction, the requests in the bids submitted by a carrier in different rounds may overlap since they are all kept alive in the auction.

Note that if the clock auction phase ends up with an efficient allocation before satisfying the stopping condition, then the CA ends without the second phase. Otherwise, the auction proceeds to the next phase, the supplementary bidding phase. Here, an efficient allocation means that all for-bid lane in the bidding pool are successfully allocated, and each for-bid lane is allocated to a unique carrier.

### **3.4.2 The supplementary bidding phase**

In the clock-proxy auction proposed by Ausubel et al. (2006), each bidder reports his values and budget constraints to a proxy who will later submit the bids to the auctioneer on behalf of the carrier, and to maximize the carrier's profit in the proxy phase. Although both clock auction and proxy auction are based on bundle bids, the clock auction phase mainly focuses on the process of price discovery while the supplementary bidding phase focus on efficient allocation. Inspired by this auction mechanism, the supplementary bidding phase of the proposed mechanisms are also focused on improving the allocation efficiency. In other words, the advantage of adding the supplementary bidding phase is that it can push the outcome of the CA towards an efficient allocation.

One way to obtain an efficient allocation is to generate as many as the bundles of requests so that one or more of them can constitute an efficient allocation. But with the limited rounds of the auction, generating too many bundles may not be practical. Therefore, reducing the overlapping and increasing the diversity of the bundles in limited rounds are important. The proposed two-phase CA mechanisms are devoted to this by generating supplementary bundles of requests in the second phase, the supplementary bidding phase.

The supplementary bundles of requests in this phase are generated following a principle, which is to involve the leftover for-bid lanes of the last round of the auction.

The two proposed mechanisms generate supplementary bundles of requests by the auctioneer and the carriers respectively. They are presented respectively in the following subsections.

#### 3.4.2.1 Supplementary bidding phase with auctioneer-generated supplementary bundles

There are three steps in this phase with auctioneer-generated supplementary bundles. The first step is that the auctioneer generates some supplementary bundles of requests open for bid. Although different rules can be used to generate the supplementary bundles, here by considering social efficiency, the auctioneer generates supplementary bundles that minimize the cost for serving the leftover lanes (the lanes that are not allocated to any carrier) after the last round of an auction. The second step is that each carrier, no matter it wins or loses in the last round of the auction, decides which supplementary bundle(s) to serve and generates a supplementary bid according to this decision. The third step is to solve a WDP by the auctioneer after collecting all supplementary bids. Note that since all the bids are kept alive during the whole process of CA, the bids in the clock auction phase and supplementary bids are all involved in this WDP.

This phase is designed based on the assumption that the information of the depot location and the number of available vehicles of each carrier is disclosed to the auctioneer. The phase will be conducted like this: when the clock phase ends, if there are some leftover lanes that are not contained in the winning bids, then the auctioneer goes to the first step and announces the supplementary bundles of lanes open for bid. The carriers then bid for the supplementary bundles in the second step. If a carrier bids for a supplementary bundle, it must serve all for-bid lanes in the bundle. Note that the tentative winning bids are also considered in this step. If a carrier decides to bid for one or multiple bundles, it then combines the bundle(s) with its tentative winning bid to form a new bid to submit. After that, the auctioneer conducts the third step and announces the winner(s) of supplementary bids (bundles).

The supplementary bidding phase may have multiple rounds. In each round of this phase, if a supplementary bundle is not bid by any carrier, the auctioneer will update the price of that bundle before proceeding to the next round. If there are some supplementary bundles bid by the carriers, then the auctioneer goes to the third step to determine the winner(s) of supplementary bids. If the solution of the winner determination problem in the third step is an efficient allocation, then the auction stops. Otherwise, proceeds to the next round by going back to the first step to generate

new supplementary bundles, and this process iterates until a prespecified stopping condition is met.

To help formulate the three steps in this phase, the following notations are introduced in advance:

---

**Indices and sets:**

$L_s$ : set of leftover lanes excluded by the tentative winning bids of last round,  $L_s \subseteq L_b$

$L_w$ : set of for-bid lanes contained in the tentative winning bid of this carrier,  $L_w \subseteq L_b$

$R_s$ : set of all supplementary bundles proposed by the auctioneer

**Parameters:**

$PS_r$ : the price of supplementary bundle  $r$ ,  $r \in R_s$

$$a_{i,j}^r = \begin{cases} 1, & \text{if lane } (i, j) \text{ is in supplementary bundle } r \\ 0, & \text{otherwise} \end{cases}, (i, j) \in L_s, r \in R_s$$

**Decision variables:**

$$b_r = \begin{cases} 1, & \text{if supplementary bundle } r \text{ is chosen to bid for} \\ 0, & \text{otherwise} \end{cases}, r \in R_s$$

$$w_{i,j}^h = \begin{cases} 1, & \text{if a leftover lane } (i, j) \text{ is served by vehicle } h \\ 0, & \text{otherwise} \end{cases}, h \in H, l \in L_s$$

---

**Step 1:** Supplementary bundle generation by the auctioneer

In the clock phase, the carriers have already expressed their willing for serving some lanes at the prices announced by the auctioneer. In the supplementary bidding phase, a price will be given to each bundle of lanes rather than each lane in the bundle in order to improve the efficiency of the auction.

The model for generating supplementary bundles of lanes by the auctioneer can be formulated as follows:

Model *SBGP-A*

$$\text{Min} \sum_{k \in K} \sum_{h \in H_k} \left( \sum_{(i,j) \in A} c_{i,j}^k x_{i,j}^{k,h} + \sum_{i \in N} f_k x_{d_k,i}^{k,h} \right)$$

s.t.

$$\sum_{k \in K} \sum_{h \in H_k} v_{i,j}^{k,h} = 1, (i, j) \in L_s \quad (3-23)$$

$$v_{i,j}^{k,h} = 0, (i, j) \in A \setminus L_s, h \in H \quad (3-24)$$

and constraint (3-1) - (3-5), (3-7) - (3-9)

In model *SBGP-A*, the auctioneer only considers the for-bid lanes that are left over according to the tentative winning bids. It is actually a BGP to minimize the total serving cost. With the information of vehicle depots of all carriers, the auctioneer generates some routes with the leftover for-bid lanes and pack the lanes in each route as a bundle, which is announced as a supplementary bundle open for bid by the carriers.

**Step 2:** Supplementary bid generation of each carrier

In this step, each carrier decides which supplementary bundle(s) of lanes provided by the auctioneer to bid for based on the tentative winning bids at the last round. If a carrier chooses some supplementary bundle(s) to bid for, the new bid it submits will be a combination of the lanes in its tentative winning bid (if any) and the lanes in the supplementary bundle.

The problem of generating a supplementary bid by a carrier can be formulated as follows:

**Model RBGP**

$$\text{Max} \sum_{h \in H} \left( \sum_{(i,j) \in L_b} v_{i,j}^h P_{i,j} - \sum_{(i,j) \in A} c_{i,j} x_{i,j}^h - \sum_{i \in N} f x_{d,i}^h \right) + \sum_{r \in R_s} b_r P S_r$$

s.t.

$$x_{i,j}^h \geq v_{i,j}^h + w_{i,j}^h, (i, j) \in A, h \in H \quad (3-25)$$

$$\sum_{h \in H} v_{i,j}^h = 1, (i, j) \in L_w \quad (3-26)$$

$$\sum_{h \in H} w_{i,j}^h = \sum_{r \in R_s} a_{i,j}^r b_r, (i, j) \in L_s \quad (3-27)$$

$$w_{i,j}^h = 0, (i, j) \in A \setminus L_s, h \in H \quad (3-28)$$

and constraint (3-11) - (3-14), (3-17) - (3-20)

Constraint (3-25) ensures the lane with requests are served. Constraint (3-26)

guarantees that the tentative winning bid is considered when resolve the BGP to decide whether or not to bid for the supplementary bundle(s) provided by the auctioneer. Constraint (3-27) ensures that if the carrier choose to bid a bundle, it must serve all the for-bid lanes in that bundle. Constraint (3-28) defines the value of binary variable  $w_{i,j}^h$  according to whether it is a leftover lane. If it is not, its value should be 0.

**Step 3:** Winner determination of the supplementary bidding phase

In this step, the auctioneer solves a WDP which is exactly the same as that in the clock auction phase except that supplementary bids are added.

After the three steps of a round in the supplementary bidding phase, if the winning bids covers all for-bid lanes, the auction ends. Otherwise, since whether a carrier decides to bid for a supplementary bundle depends on its price, the prices of the bundles will be adjusted. If a supplementary bundle is not bid by any carrier in step 2, the auctioneer will increase the price of this bundle in the next round. The upper bound of the price of the supplementary bundle is the sum of the revenue of all requests contained in this bundle. The above three steps iterate until  $L_s = \emptyset$ , which implies that each for-bid lane is allocated to and served by a unique carrier, or a pre-set number of rounds is reached.

3.4.2.2 Supplementary bidding phase with carrier-generated supplementary bids

Different from the above supplementary bidding phase that the auctioneer generates supplementary bundles for the carrier to choose, in this mechanism, the carriers directly generate supplementary bids themselves. The supplementary bids are also generated based on the results of the clock auction phase.

There are two steps in each round of this phase with carrier-generated supplementary bids. The first step is that each carrier generates a supplementary bid based on the results of the last round to minimize its net profit for serving the chosen lanes. The difference between the supplementary bids generated in this supplementary phase and the bids generated in the clock auction phase is that, in this phase, the new-generated supplementary bid must contain both the tentative winning lanes (if any) and at least one leftover for-bid lane which is not in any tentative winning bid. The second step is that the auctioneer solves a WDP after collecting new supplementary bids. This is the same as the supplementary bidding phase with auctioneer-generated supplementary bundles, where the bids in the clock auction

phase are also involved in this WDP.

The phase will be conducted like this: when the clock phase ends, if there are some leftover lanes that are not contained in the winning bids, and a carrier has no supplementary bid in the bidding pool, then this carrier goes to the first step and generate a supplementary bid and submits it to the auctioneer. Then, the auctioneer conducts the second step after collecting the supplementary bids from all carriers and announces the winner(s) of supplementary bids.

This supplementary bidding phase may also have multiple rounds. In each round of this phase, if a supplementary bid of a carrier is not a winning bid in the WDP, then this carrier updates the price of that bid before proceeding to the next round. A more detailed introduction of the two steps and their related mathematical models is given in the following.

**Step 1:** Supplementary bid generation by each carrier

In this step, each carrier generates a supplementary bid based on the results of the last round of an auction. If a carrier wins a bid in the last round, then it generates a supplementary bid containing both the for-bid lanes in its winning bid and at least one leftover lane. If a carrier loses in the last round, its generated supplementary bid only needs to contain one or more lanes selected from the leftover lanes.

The model for generating a supplementary bid of a carrier can be formulated as follows:

Model *SBGP-C*

$$\text{Max} \sum_{h \in H} \left( \sum_{(i,j) \in L_w} v_{i,j}^h P_{i,j} + \sum_{(i,j) \in L_s} w_{i,j}^h P_{i,j} - \sum_{(i,j) \in A} c_{i,j} x_{i,j}^h - \sum_{i \in N} f x_{d,i}^h \right)$$

s.t.

$$\sum_{h \in H} w_{i,j}^h \leq 1; (i,j) \in L_s \quad (3-29)$$

$$\sum_{(i,j) \in L_s} \sum_{h \in H} w_{i,j}^h > 0 \quad (3-30)$$

and constraint (3-11) – (3-14), (3-17) - (3-20), (3-25) - (3-26), (3-28)

Constraint (3-29) indicates that for each leftover lane, it can be served by the carrier at most once. And constraint (3-30) ensures that the carrier will choose at least a leftover lane in its supplementary bid.

**Step 2:** Winner determination of the supplementary bidding phase

In this step, the auctioneer solves a WDP which is exactly the same as that in the supplementary bidding phase with auctioneer-generated supplementary bundles.

After the two steps of a round in the supplementary bidding phase, if the winning bids covers all for-bid lanes, the auction ends. Otherwise, the prices of the supplementary bids will be adjusted. If a supplementary bid is not a winning bid in the WDP in step 2, the carrier will decrease the price of this bid in the next round. The lower bound of the price of the supplementary bid is the travelling cost of the route(s) that contains all requests in this bid. The above two steps iterate until  $L_s = \emptyset$ , which implies that each for-bid lane is allocated to and served by a unique carrier or pre-set number of rounds is reached.

To well understand the two-phase mechanisms, a visualized description of the clock auction phase and the two types of supplementary bidding phase are provided. Fig. 3-1 illustrates the process of the clock auction phase, Fig 3-2 shows how the supplementary bidding phase with auctioneer-generated supplementary bundles works, and Fig. 3-3 demonstrates the process of the supplementary bidding phase with supplementary bids generated by the carriers. The combination of the processes in Fig.3-1 and Fig. 3-2 generates the whole process of the two-phase CA mechanism with auctioneer-generated supplementary bundles, whereas the combination of the processes in Fig. 3-1 and Fig. 3-3 generates the whole process of the two-phase CA mechanism with supplementary bids generated by the carriers.

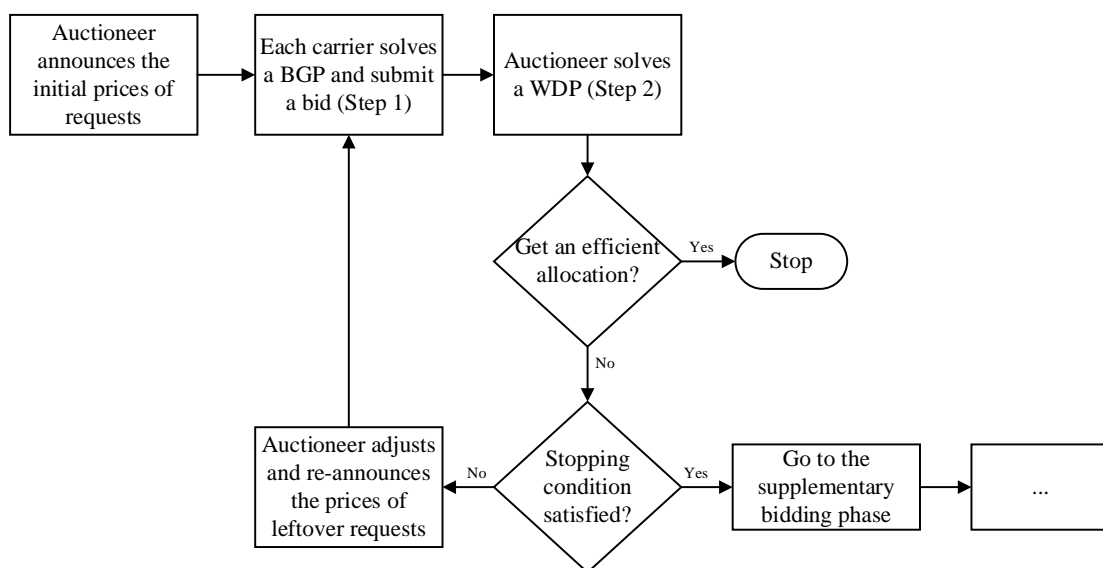


Figure 3-1 Clock auction phase

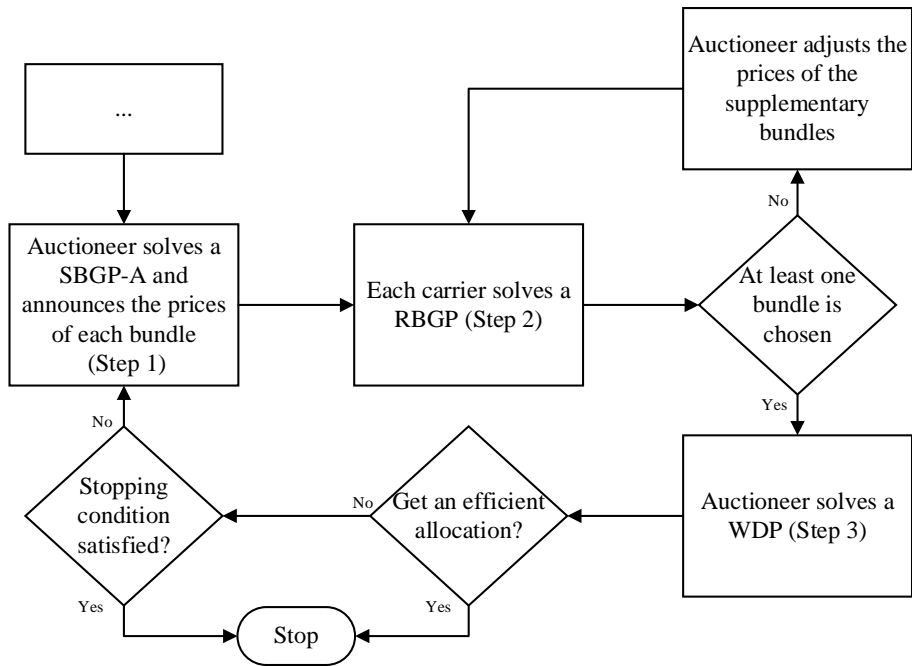


Figure 3-2 Supplementary bidding phase with auctioneer-generated supplementary bundles

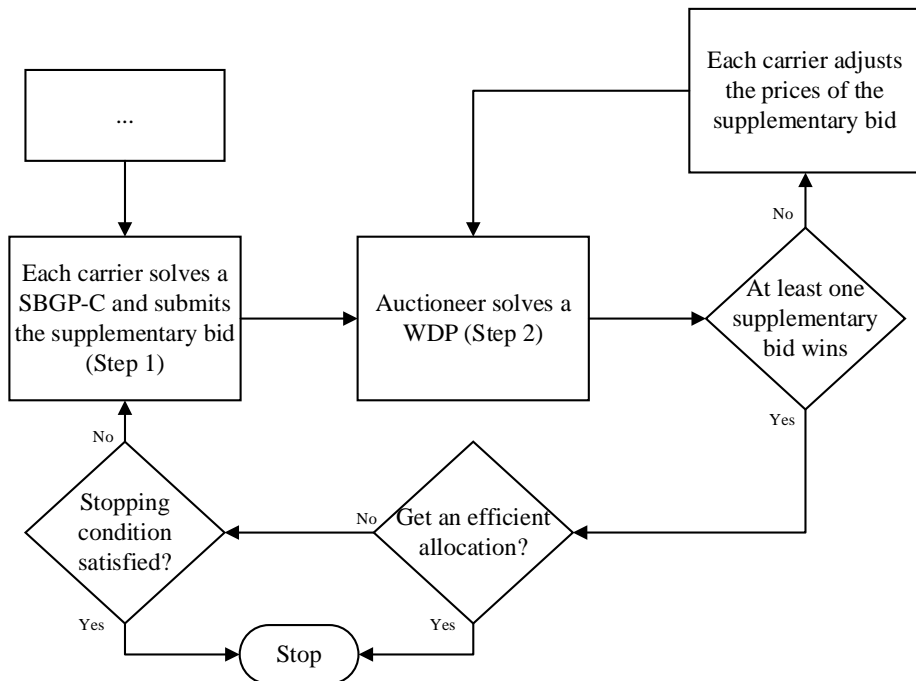


Figure 3-3 Supplementary bidding phase with carrier-generated supplementary bids



### 3.5 Mechanism evaluation by computational experiments

In this section the efficiency of the proposed two-phase CA mechanisms and related models is evaluated by numerical experiments on randomly generated instances. All the models are coded in C++ and solved by CPLEX. The solution and objective value of the centralized mathematical programming model solved by CPLEX solver are used as a benchmark for evaluating the efficiency of the proposed mechanisms. The advantage of the two-phase CA mechanisms over the clock auction is also discussed through comparison. All the tests are conducted on a PC with Intel® Core™ i7-8750H CPU and 16 GB RAM. The version of CPLEX is 12.10.0.0 for 64-bit Windows.

#### 3.5.1 Parameter setting

For the convenience of presentation, hereafter, the two-phase CA mechanisms will be referred respectively to TPCAMA which is the two-phase CA mechanism with auctioneer-generated supplementary bundles and to TPCAMC which is the two-phase CA mechanism with the supplementary bid generated by the carriers.

The parameters used in the experiments are listed in Table 3-1. In the parameter setting, there are some points need to be noted.

(1) For simplicity, both the travel time between the origin and the destination of lane  $(i, j)$  and the cost of travelling through the lane  $(i, j)$  are set to its Euclidean distance.

(2) The revenue of each request is set as in the table to avoid the situation that some lanes are outsourced at a loss to carriers by the auctioneer since the centralized model will outsource all the for-bid lanes compulsively. With this setting, in the worst case, each lane can be allocated to the carrier whose cost of serving only this lane by a single vehicle is no higher than its revenue in the CA mechanisms.

(3)  $\Delta$  in the table is the minimum increment of the price of a lane or a bundle of lanes in each round of an auction. For real instances,  $\Delta$  needs to be set as small as possible to seek for an efficient or a nearly efficient allocation. However, for small size instances tested, the proposed two-phase CA can obtain an optimal or nearly optimal allocation with a relatively big  $\Delta$ . Note that due to the high computational complexity of the centralized planning model, only small size instances are tested to evaluate the efficiency of our two two-phase CA mechanisms.

(4) In reality, the cost/travel time, the fixed cost and the maximum duration of a route may vary with different vehicles/routes of different carriers, which is reflected

in the above models. In Table 3-1, the vehicle superscript  $k$  in  $t_{i,j}^k, c_{i,j}^k$  is retained to indicate this dependence. However, in our numerical experiments, they are set as identical among the vehicles for the sake of simplicity.

Table 3-1 Parameter values for the generation of the instances

Parameter	Value
Number of for-bid lanes	20~30% $N^2$
Initial price $P_{i,j}$ of lane $(i, j)$	0
Coordinates $(x_k, y_k)$ of the depot of each carrier $k \in K$	$U[0, 100] \times [0, 100]$
Coordinates $(x_i, y_i)$ of each node $i \in N$	$U[0, 100] \times [0, 100]$
$t_{i,j}^k, c_{i,j}^k$	$\sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$
Revenue of a request (lane) $(i, j)$	$\sum_{k \in K} (c_{d,i}^k + c_{i,j}^k + c_{j,d'}^k) / K + f_k + 1$
$\Delta$ : the minimum increment of the price of a lane $(i, j)$ in each round	10
$\Delta$ : the minimum increment of the price of a bundle of lanes in each round	10
Fixed cost $f_k$	30
Maximum duration $B$ of each route	1410
Maximum number of rounds for CA	50

In the following parts, the proposed two-phase mechanisms will be evaluated by comparing their outcomes with the solution of the centralized mathematical programming model and the outcome of the clock auction. The performance indexes used in this evaluation include the social efficiency of the allocation obtained by each approach, the CPU time to obtain an optimal or near-optimal allocation, the number of rounds required for obtaining an efficient allocation, and the total procurement/outsourcing cost of the shippers (the auctioneer). To facilitate the presentation of the computational results, these performance indexes and their descriptions are given in Table 3-2.

Table 3-2 Description of the performance indexes

Index	Description
$C_{\text{approach}}$	The total cost obtained from the corresponding approach
$R_{\text{approach}}$	The number of rounds needed for getting an efficient allocation
$A_{\text{approach}}$	The total outsourcing cost of the auctioneer
$GC_{\text{approach2/approach1}}$	Gap of the objective value, $(C_{\text{approach2}} - C_{\text{approach1}}) / C_{\text{approach1}}$
$GA_{\text{approach2/approach1}}$	Gap of the outsourcing cost of the auctioneer, $(A_{\text{approach2}} - A_{\text{approach1}}) / A_{\text{approach1}}$

In Table 3-2, “approach” means the approach used, which can be CP, CL, TPA

and TPC. CP denotes the centralized planning approach, CL denotes the clock auction, TPA and TPC denote the two-phase CA mechanisms TPCAMA and TPCAMC respectively.

### 3.5.2 Comparison with the centralized planning approach

The first group of tests are used to evaluate the proposed two-phase mechanisms by comparing their solutions with that obtained by solving the centralized planning model.

In this group of tests, 3 sets of instances with the number of nodes  $N = 5, 6$  and  $7$  are tested respectively. The number of carriers is set as  $K = 3$ , and the number of vehicles each carrier has for the CA is set as  $H = 3$ . For this group of tests, each instance is identified by its number of nodes, vehicles and carriers, and its serial number. For example, instance 533-1 represents the first instance with 5 nodes, 3 carriers and 3 vehicles for each carrier. Note that repetitive lanes are discarded when randomly generating for-bid lanes, the real number of for-bid lanes may be less than the number calculated directly. In this group of tests, the number of rounds for the clock auction phase is set as 20. That is, if the clock auction phase cannot find an efficient allocation of the for-bid lanes, then the CA will go into the supplementary bidding phase.

Table 3-3 presents the results of the 3 sets of instances with the total cost of the carriers including the cost to serve all lanes for-bid lanes and the cost for empty vehicle repositioning. The relative gap of the total cost between each proposed mechanism and the centralized planning approach is also presented.

Table 3-3 Results of the proposed mechanisms versus the centralized planning approach

Instance	$C_{CP}$	$C_{TPA}$	$GC_{TPA/CP}$	$C_{TPC}$	$GC_{TPC/CP}$
533-1	461.706	461.706	0.00%	461.706	0.00%
533-2	623.227	628.907	0.91%	628.907	0.91%
533-3	765.338	781.825	2.15%	781.825	2.15%
533-4	615.196	620.116	0.80%	620.116	0.80%
533-5	426.256	426.256	0.00%	426.256	0.00%
533-6	623.525	623.525	0.00%	623.525	0.00%
533-7	579.813	579.813	0.00%	579.813	0.00%
533-8	557.571	557.571	0.00%	557.571	0.00%
533-9	600.513	604.716	0.70%	604.716	0.70%
533-10	754.097	754.097	0.00%	754.097	0.00%
<b>Average</b>			<b>0.46%</b>		<b>0.46%</b>
633-1	694.277	694.277	0.00%	694.277	0.00%
633-2	822.448	850.064	3.36%	850.064	3.36%

<b>Instance</b>	$C_{CP}$	$C_{TPA}$	$GC_{TPA/CP}$	$C_{TPC}$	$GC_{TPC/CP}$
633-3	884.439	884.439	0.00%	884.439	0.00%
633-4	716.263	718.570	0.32%	718.570	0.32%
633-5	570.229	570.229	0.00%	570.229	0.00%
633-6	833.738	877.688	5.27%	874.482	4.89%
633-7	721.396	738.992	2.44%	738.992	2.44%
633-8	806.865	814.482	0.94%	814.482	0.94%
633-9	803.133	842.053	4.85%	850.587	5.91%
633-10	912.282	975.824	6.97%	975.824	6.97%
<b>Average</b>			<b>2.41%</b>		<b>2.48%</b>
733-1	744.369	744.369	0.00%	744.369	0.00%
733-2	898.418	898.418	0.00%	898.418	0.00%
733-3	713.332	713.820	0.07%	713.820	0.07%
733-4	617.767	659.136	6.70%	659.136	6.70%
733-5	606.683	612.750	1.00%	612.75	1.00%
733-6	691.814	691.814	0.00%	696.928	0.74%
733-7	778.853	800.160	2.74%	800.160	2.74%
733-8	820.654	836.672	1.95%	836.672	1.95%
733-9	734.554	744.903	1.41%	744.903	1.41%
733-10	858.936	869.019	1.17%	869.019	1.17%
<b>Average</b>			<b>1.50%</b>		<b>1.58%</b>

The results in Table 3-3 show that both the proposed two-phase CA mechanisms can obtain an optimal or nearly optimal allocation for all the instances. The relative gap for the total cost is smaller than 3%. Since the centralized planning approach is in fact unpractical, this performance is good enough for practical application.

### 3.5.3 Comparison with clock auction

The purpose of introducing the supplementary bidding phase after the clock auction phase is to improve the social efficiency of allocation since the price discovery process of clock auction can be very slow sometimes. This part evaluated the proposed two-phase mechanisms by comparing their performances with clock auction only. The time to go to the supplementary bidding phase is also discussed.

To compare the proposed CA mechanisms with only the clock auction, the results of the tests using the clock auction are firstly presented in Table 3-4. The instances here are the same as the instances in subsection 3.4.2. The maximum number of rounds of the clock auction is set to 50.

It can be observed from Table 3-4 that the clock auction needs many rounds to get an optimal or near optimal solution with a gap to the centralized model less than 2%. Among the instances tested, 3 instances, whose  $R_{CL}$  are marked with two hyphens,

cannot get an efficient allocation within 50 rounds.

Table 3-4 Results of the clock auction

<b>Instance</b>	<b><math>C_{CL}</math></b>	<b><math>A_{CL}</math></b>	<b><math>R_{CL}</math></b>	<b><math>GC_{CL/CP}</math></b>
533-1	461.706	490	14	0.00%
533-2	623.277	660	31	0.01%
533-3	765.338	800	29	0.00%
533-4	617.503	640	24	0.38%
533-5	426.256	460	18	0.00%
533-6	623.525	640	28	0.00%
533-7	581.247	590	29	0.25%
533-8	557.571	580	19	0.00%
533-9	604.716	620	29	0.70%
533-10	754.097	767.859	33	0.00%
<b>Average</b>				<b>0.13%</b>
633-1	719.493	770	24	3.63%
633-2	870.909	886.777	--	5.89%
633-3	884.439	930	18	0.00%
633-4	718.570	740	22	0.32%
633-5	570.229	620	16	0.00%
633-6	878.720	887.286	--	5.40%
633-7	725.200	740	27	0.53%
633-8	807.495	840	46	0.08%
633-9	803.133	850	23	0.00%
633-10	925.488	960	41	1.45%
<b>Average</b>				<b>1.73%</b>
733-1	757.400	800	32	1.75%
733-2	902.749	940	39	0.48%
733-3	713.332	730	29	0.00%
733-4	617.767	640	22	0.00%
733-5	612.750	650	19	1.00%
733-6	696.928	709.699	47	0.74%
733-7	799.651	810	39	2.67%
733-8	829.685	850	40	1.10%
733-9	743.310	770	40	1.19%
733-10	878.610	885.025	--	2.29%
<b>Average</b>				<b>1.12%</b>

From the results in Table 3-4, it can be observed that the clock auction can get an efficient allocation for most of the tested instances within 50 rounds. But in reality, even one single round of auction can take a very long time, let alone tens of round. The maximum number of rounds may be limit to a relatively small number. Therefore, the two-phase mechanisms can be significant in getting an efficient allocation within

less rounds of CA. In the following, the experiments with different number of rounds of the clock auction phase are conducted to reveal the advantages of the proposed two-phase CA mechanisms.

In this group of tests, 4 sets of instances with the number of  $N = 6$  and  $7$ ,  $H = 3$ ,  $K = 3$  are conducted. The maximum number of rounds of the CA is set to 50, which include rounds in the clock auction phase and the rounds in the supplementary bidding phase. To evaluate the effectiveness of the two-phase CA mechanisms in obtaining an optimal or near-optimal allocation in a fixed number of rounds 50, different maximum numbers of rounds are set for the clock auction phase, which are 10, 20, 30 and 40, respectively. This means that the clock auction phase of the two-phase CA mechanism will stop if a pre-set maximum number of rounds 10, 20, 30 or 40 is reached. After the clock auction, the remaining rounds ( $50 -$  the number of rounds spent on the clock auction) are dedicated to supplementary bidding rounds in the second phase of our two-phase CA mechanisms. The instances in this group are identified by its number of nodes, vehicles and carriers, the number of rounds that the clock auction stops, and its serial number. For example, instance 633-10-1 represents the first instance with 6 nodes, 3 carriers and 3 vehicles for each carrier, and the clock auction phase stops after 10 rounds no matter whether the allocation of the for-bid lanes is efficient or not.

Table 3-5 and Table 3-6 present the results of this group of instances. The total cost, the number of rounds required to obtain an efficient allocation, the procurement/outsourcing cost of the auctioneer for the clock auction only and for the two-phase CA mechanisms are presented as well as the corresponding relative gap of total cost. Note the performance indexes of the clock auction here is those obtained when the clock auction phase of a two-phase CA mechanism stops.

The results in Table 3-5 and Table 3-6 can be interpreted from several aspects.

Firstly, from the number of rounds to obtain an efficient allocation, it can be observed that no matter when the clock auction stops, both the two-phase CA mechanisms can obtain an efficient allocation in a few rounds after going into the supplementary bidding phase. Compared with TPCAMA, TPCAMC can obtain an efficient allocation with less rounds. In fact, no matter how many rounds the clock auction phase is conducted, TPCAMC can obtain an efficient allocation within 3 rounds. This may be because the sizes of the instances are not large, but it can prove the efficiency of TPCAMC in time. In addition, for TPCAMA, the more rounds the clock auction phase is conducted, the quicker the supplementary bidding phase can find an efficient allocation.

Secondly, from the relative gap of total cost with respect to the centralized planning approach, which reflects the social efficiency of an allocation obtained, it can be observed from Table 3-5 and Table 3-6 that the relative cost gap between the allocation obtained by the clock auction phase and that obtained by TPCAMA or TPCAMC is relatively large. The earlier the clock auction phase stops, the larger the gap is. That is because if the clock auction phase stops without an efficient allocation, the leftover for-bid lanes are treated as if each of them is served by a single vehicle with the service cost equal to the revenue of the lane. Hence, with the introduction of the supplementary bidding phase, the total cost can quickly get close to its optimal value. Comparing  $GC_{TPA/CL}$  and  $GC_{TPC/CL}$  as well as  $GC_{TPA/CP}$  and  $GC_{TPC/CP}$  in Table 3-5 and Table 3-6, TPCAMA slightly outperforms TPCAMC in obtaining a better allocation. However, for both TPCAMA and TPCAMC, the earlier the clock auction phase stops, the more advantage the two-phase CA mechanisms have.

Finally, from the procurement/outsourcing cost of the auctioneer, it can be observed that by introducing the supplementary bidding phase, both TPCAMA and TPCAMC can save the outsourcing cost of the auctioneer. TPCAMC performs better than TPCAMA in terms of this cost since its supplementary bidding phase is a process with the decreasing of bid prices in each round, while the supplementary bidding phase of TPCAMA is a process with the increasing of supplementary bundle price in each round.

From this group of tests, it can also be observed that with the increase of the number of rounds of the clock auction, the total cost of the allocation obtained by each of the two two-phase CA mechanisms usually gets closer to its optimal value, but this is not always the case. The CA with 40 rounds of clock auction phase may not perform better than that with 30 rounds of clock auction phase for some instances. This is because the price discovery process of the clock auction may not converge with the prices of some lanes alternatively increasing and decreasing in consecutive rounds.

To sum up, both TPCAMA and TPCAMC perform well in obtaining efficient allocations compared to the centralized planning approach. Compared with the clock auction, the two-phase CA mechanisms can accelerate the CA process and perform better in finding an efficient allocation within a limited number of rounds. They can also save the procurement outsourcing cost for the auctioneer. Relatively, TPCAMA can obtain an efficient allocation closer to the optimal allocation than TPCAMC, but TPCAMC is more timesaving and cost-saving for the auctioneer. Note that the lower

bound for the bid of each supplementary bundle of requests in TPCAMC is set by considering the worst case that each carrier has no profit to bid for this bundle with its bidding price given by the lower bound. If this lower bound is increased, the advantage of cost-saving of TPCAMC over TPCAMA may be weakened. In conclusion, the proposed two-phase CA mechanisms are efficient both in time and allocation.

Table 3-5 Two-phase CA mechanism TPCAMA and the clock auction

Instance	$C_{CL}$	$C_{TPA}$	$GC_{TPA/CL}$	$GC_{TPA/CP}$	$A_{CL}$	$A_{TPA}$	$GA_{TPA/CL}$	$R_{CL}$	$R_{TPA}$
633-10-1	909.220	694.277	-23.64%	0.00%	941.599	730	-22.47%	--	14
633-10-2	1119.94	861.431	-23.08%	4.74%	1124.51	870	-22.63%	--	17
633-10-3	1406.72	888.137	-36.86%	0.42%	1442.75	940	-34.85%	--	19
633-10-4	874.688	718.570	-17.85%	0.32%	893.867	740	-17.21%	--	16
633-10-5	858.918	579.968	-32.48%	1.71%	910.815	640	-29.73%	--	18
633-10-6	1233.22	861.912	-30.11%	3.38%	1244.83	890	-28.50%	--	16
633-10-7	906.509	812.079	-10.42%	12.57%	926.969	840	-9.38%	--	17
633-10-8	1309.84	806.865	-38.40%	0.00%	1344.55	860	-36.04%	--	17
633-10-9	1202.67	842.053	-29.98%	4.85%	1222.87	880	-28.04%	--	15
633-10-10	1350.28	912.818	-32.40%	0.06%	1359.56	940	-30.86%	--	17
<b>Average</b>			<b>-27.52%</b>	<b>2.80%</b>			<b>-25.97%</b>		
633-20-1	798.484	694.277	-13.05%	0.00%	856.548	760	-11.27%	--	22
633-20-2	861.976	850.064	-1.38%	3.36%	896.777	890	-0.76%	--	25
633-20-3	884.439	884.439	0.00%	0.00%	930	930	0.00%	18	18
633-20-4	874.688	718.570	-17.85%	0.32%	893.867	760	-14.98%	--	21
633-20-5	570.229	570.229	0.00%	0.00%	620	620	0.00%	16	16
633-20-6	881.722	877.688	-0.46%	5.27%	907.286	907.286	0.00%	--	29
633-20-7	802.661	738.992	-7.93%	2.44%	838.538	780	-6.98%	--	27
633-20-8	867.934	814.482	-6.16%	0.94%	906.128	860	-5.09%	--	23
633-20-9	872.634	842.053	-3.50%	4.85%	916.314	890	-2.87%	--	27
633-20-10	997.253	975.824	-2.15%	6.97%	1020.84	1000	-2.04%	--	28
<b>Average</b>			<b>-5.25%</b>	<b>2.41%</b>			<b>-4.40%</b>	<b>--</b>	
633-30-1	719.493	719.493	0.00%	3.63%	770	770	0.00%	24	24
633-30-2	853.473	827.971	-2.99%	0.67%	886.777	870	-1.89%	--	34
633-30-3	884.439	884.439	0.00%	0.00%	930	930	0.00%	18	18
633-30-4	718.570	718.570	0.00%	0.32%	740	740	0.00%	22	22
633-30-5	570.229	570.229	0.00%	0.00%	620	620	0.00%	16	16
633-30-6	878.720	877.485	-0.14%	5.25%	887.286	887.286	0.00%	--	37
633-30-7	725.200	725.200	0.00%	0.53%	740	740	0.00%	27	27
633-30-8	860.947	807.495	-6.21%	0.08%	886.128	840	-5.21%	--	32
633-30-9	803.133	803.133	0.00%	0.00%	850	850	0.00%	23	23
633-30-10	990.601	912.818	-7.85%	0.06%	1020.84	950	-6.94%	--	33
<b>Average</b>			<b>-1.72%</b>	<b>1.05%</b>			<b>-1.40%</b>	<b>--</b>	
633-40-1	719.493	719.493	0.00%	3.63%	770	770	0.00%	24	24
633-40-2	870.909	858.997	-1.37%	4.44%	886.777	880	-0.76%	--	44



Instance	$C_{CL}$	$C_{TPA}$	$GC_{TPA/CL}$	$GC_{TPA/CP}$	$A_{CL}$	$A_{TPA}$	$GA_{TPA/CL}$	$R_{CL}$	$R_{TPA}$
633-40-3	884.439	884.439	0.00%	0.00%	930	930	0.00%	18	18
633-40-4	718.570	718.570	0.00%	0.32%	740	740	0.00%	22	22
633-40-5	570.229	570.229	0.00%	0.00%	620	620	0.00%	16	16
633-40-6	878.720	877.485	-0.14%	5.25%	887.286	887.286	0.00%	--	46
633-40-7	725.200	725.200	0.00%	0.53%	740	740	0.00%	27	27
633-40-8	860.947	807.495	-6.21%	0.08%	886.128	840	-5.21%	--	42
633-40-9	803.133	803.133	0.00%	0.00%	850	850	0.00%	23	23
633-40-10	990.601	912.818	-7.85%	0.06%	1020.84	950	-6.94%	--	42
<b>Average</b>			<b>-1.56%</b>	<b>1.43%</b>			<b>-1.29%</b>		
733-10-1	948.648	744.369	-21.53%	0.00%	950.155	760	-20.01%	--	17
733-10-2	1122.57	898.418	-19.97%	0.00%	1158.31	940	-18.85%	--	25
733-10-3	969.964	713.332	-26.46%	0.00%	971.902	720	-25.92%	--	17
733-10-4	952.489	659.136	-30.80%	6.70%	969.851	680	-29.89%	--	15
733-10-5	704.786	627.179	-11.01%	3.38%	729.351	660	-9.51%	--	13
733-10-6	835.178	709.205	-15.08%	2.51%	837.162	719.699	-14.03%	--	18
733-10-7	1187.60	867.522	-26.95%	11.38%	1199.6	770	-35.81%	--	26
733-10-8	965.581	829.685	-14.07%	1.10%	972.451	850	-12.59%	--	23
733-10-9	925.974	762.815	-17.62%	3.85%	934.657	780	-16.55%	--	16
733-10-10	990.954	868.483	-12.36%	1.11%	998.845	890	-10.90%	--	25
<b>Average</b>			<b>-19.95%</b>	<b>3.00%</b>			<b>-19.41%</b>		
733-20-1	774.833	744.369	-3.93%	0.00%	826.185	800	-3.17%	--	24
733-20-2	918.051	898.418	-2.14%	0.00%	947.452	930	-1.84%	--	28
733-20-3	727.102	713.820	-1.83%	0.07%	734.495	730	-0.61%	--	25
733-20-4	715.739	659.136	-7.91%	6.70%	739.503	690	-6.69%	--	25
733-20-5	612.750	612.750	0.00%	1.00%	650	650	0.00%	19	19
733-20-6	697.678	691.814	-0.84%	0.00%	729.699	729.699	0.00%	--	24
733-20-7	814.108	800.160	-1.71%	2.74%	830.735	820	-1.29%	--	27
733-20-8	859.035	836.672	-2.60%	1.95%	867.379	850	-2.00%	--	28
733-20-9	760.872	744.903	-2.10%	1.41%	772.575	760	-1.63%	--	26
733-20-10	878.610	869.019	-1.09%	1.17%	885.025	890	0.56%	--	26
<b>Average</b>			<b>-2.42%</b>	<b>1.50%</b>			<b>-1.67%</b>		
733-30-1	774.833	744.369	-3.93%	0.00%	826.185	800	-3.17%	--	32
733-30-2	918.051	898.418	-2.14%	0.00%	947.452	930	-1.84%	--	35
733-30-3	713.332	713.332	0.00%	0.00%	730	730	0.00%	29	29
733-30-4	617.767	617.767	0.00%	0.00%	640	640	0.00%	22	22
733-30-5	612.750	612.750	0.00%	1.00%	650	650	0.00%	19	19
733-30-6	697.678	691.814	-0.84%	0.00%	709.699	709.699	0.00%	--	32
733-30-7	814.108	800.160	-1.71%	2.74%	820.735	810	-1.31%	--	34
733-30-8	859.035	836.672	-2.60%	1.95%	867.379	850	-2.00%	--	33
733-30-9	760.872	744.903	-2.10%	1.41%	772.575	760	-1.63%	--	32
733-30-10	878.610	869.019	-1.09%	1.17%	885.025	880	-0.57%	--	35
<b>Average</b>			<b>-1.44%</b>	<b>0.83%</b>			<b>-1.05%</b>		
733-40-1	757.400	757.400	0.00%	1.75%	800	800	0.00%	32	32

Instance	$C_{CL}$	$C_{TPA}$	$GC_{TPA/CL}$	$GC_{TPA/CP}$	$A_{CL}$	$A_{TPA}$	$GA_{TPA/CL}$	$R_{CL}$	$R_{TPA}$
733-40-2	902.749	902.749	0.00%	0.48%	940	940	0.00%	39	39
733-40-3	713.332	713.332	0.00%	0.00%	730	730	0.00%	29	29
733-40-4	617.767	617.767	0.00%	0.00%	640	640	0.00%	22	22
733-40-5	612.750	612.750	0.00%	1.00%	650	650	0.00%	19	19
733-40-6	696.928	696.928	0.00%	0.74%	709.699	709.699	0.00%	39	39
733-40-7	799.651	799.651	0.00%	2.67%	810	810	0.00%	39	39
733-40-8	829.685	829.685	0.00%	1.10%	850	850	0.00%	40	40
733-40-9	741.310	741.310	0.00%	0.92%	770	770	0.00%	40	40
733-40-10	878.074	869.019	-1.03%	1.17%	885.025	880	-0.57%	--	43
<b>Average</b>			<b>-0.10%</b>	<b>0.98%</b>			<b>-0.06%</b>		

Table 3-6 Two-phase CA mechanism TPCAMC and the clock auction

Instance	$C_{CL}$	$C_{TPC}$	$GC_{TPC/CL}$	$GC_{TPC/CP}$	$A_{CL}$	$A_{TPC}$	$GA_{TPC/CL}$	$R_{CL}$	$R_{TPC}$
633-10-1	909.220	784.252	-13.74%	12.96%	941.599	816.63	-13.27%	--	11
633-10-2	1119.94	895.876	-20.01%	8.93%	1124.51	896.646	-20.26%	--	12
633-10-3	1406.72	888.137	-36.86%	0.42%	1442.75	888.137	-38.44%	--	12
633-10-4	874.688	718.570	-17.85%	0.32%	893.867	723.164	-19.10%	--	11
633-10-5	858.918	619.720	-27.85%	8.68%	910.815	619.72	-31.96%	--	11
633-10-6	1233.22	868.223	-29.60%	4.14%	1244.83	868.223	-30.25%	--	12
633-10-7	906.509	812.079	-10.42%	12.57%	926.969	826.185	-10.87%	--	12
633-10-8	1309.84	806.865	-38.40%	0.00%	1344.55	806.865	-39.99%	--	13
633-10-9	1202.67	842.053	-29.98%	4.85%	1222.87	842.053	-31.14%	--	12
633-10-10	1350.28	1034.46	-23.39%	13.39%	1359.56	1034.46	-23.91%	--	13
<b>Average</b>			<b>-24.81%</b>	<b>6.63%</b>			<b>-25.92%</b>		
633-20-1	798.484	694.277	-13.05%	0.00%	856.548	740	-13.61%	--	21
633-20-2	861.976	850.064	-1.38%	3.36%	896.777	862.192	-3.86%	--	21
633-20-3	884.439	884.439	0.00%	0.00%	930	930	0.00%	18	18
633-20-4	874.688	718.570	-17.85%	0.32%	893.867	740	-17.21%	--	21
633-20-5	570.229	570.229	0.00%	0.00%	620	620	0.00%	16	16
633-20-6	881.722	874.482	-0.82%	4.89%	907.286	891.433	-1.75%	--	21
633-20-7	802.661	738.992	-7.93%	2.44%	838.538	738.992	-11.87%	--	21
633-20-8	867.934	814.482	-6.16%	0.94%	906.128	830	-8.40%	--	21
633-20-9	872.634	850.587	-2.53%	5.91%	916.314	858.817	-6.27%	--	21
633-20-10	997.253	975.824	-2.15%	6.97%	1020.84	983.161	-3.69%	--	21
<b>Average</b>			<b>-5.19%</b>	<b>2.48%</b>			<b>-6.67%</b>		
633-30-1	719.493	719.493	0.00%	3.63%	770	770	0.00%	24	24
633-30-2	853.473	827.971	-2.99%	0.67%	886.777	827.971	-6.63%	--	31
633-30-3	884.439	884.439	0.00%	0.00%	930	930	0.00%	18	18
633-30-4	718.570	718.570	0.00%	0.32%	740	740	0.00%	22	22
633-30-5	570.229	570.229	0.00%	0.00%	620	620	0.00%	16	16
633-30-6	878.720	874.685	-0.46%	4.91%	887.286	876.3	-1.24%	--	31
633-30-7	725.200	725.200	0.00%	0.53%	740	740	0.00%	27	27

Instance	$C_{CL}$	$C_{TPC}$	$GC_{TPC/CL}$	$GC_{TPC/CP}$	$A_{CL}$	$A_{TPC}$	$GA_{TPC/CL}$	$R_{CL}$	$R_{TPC}$
633-30-8	860.947	807.495	-6.21%	0.08%	886.128	812.819	-8.27%	--	31
633-30-9	803.133	803.133	0.00%	0.00%	850	850	0.00%	23	23
633-30-10	990.601	912.818	-7.85%	0.06%	1020.84	912.818	-10.58%	--	31
<b>Average</b>			<b>-1.75%</b>	<b>1.02%</b>			<b>-2.67%</b>		--
633-40-1	719.493	719.493	0.00%	3.63%	770	770	0.00%	24	24
633-40-2	870.909	871.381	0.05%	5.95%	886.777	873.509	-1.50%	--	41
633-40-3	884.439	884.439	0.00%	0.00%	930	930	0.00%	18	18
633-40-4	718.570	718.570	0.00%	0.32%	740	740	0.00%	22	22
633-40-5	570.229	570.229	0.00%	0.00%	620	620	0.00%	16	16
633-40-6	878.720	874.685	-0.46%	4.91%	887.286	876.3	-1.24%	--	41
633-40-7	725.200	725.200	0.00%	0.53%	740	740	0.00%	27	27
633-40-8	860.947	807.495	-6.21%	0.08%	886.128	820	-7.46%	--	41
633-40-9	803.133	803.133	0.00%	0.00%	850	850	0.00%	23	23
633-40-10	990.601	912.818	-7.85%	0.06%	1020.84	912.818	-10.58%	--	41
<b>Average</b>			<b>-1.45%</b>	<b>1.55%</b>			<b>-2.08%</b>		
733-10-1	948.648	744.369	-21.53%	0.00%	950.155	744.369	-21.66%	--	13
733-10-2	1122.57	898.418	-19.97%	0.00%	1158.31	898.418	-22.44%	--	12
733-10-3	969.964	713.332	-26.46%	0.00%	971.902	713.332	-26.60%	--	12
733-10-4	952.489	659.136	-30.80%	6.70%	969.851	676.499	-30.25%	--	12
733-10-5	704.786	645.425	-8.42%	6.39%	729.351	656.261	-10.02%	--	11
733-10-6	835.178	709.205	-15.08%	2.51%	837.162	711.189	-15.05%	--	12
733-10-7	1187.60	798.351	-32.78%	2.50%	1199.6	809.26	-32.54%	--	12
733-10-8	965.581	836.672	-13.35%	1.95%	972.451	843.542	-13.26%	--	12
733-10-9	925.974	770.627	-16.78%	4.91%	934.657	770.627	-17.55%	--	12
733-10-10	990.954	868.483	-12.36%	1.11%	998.845	876.373	-12.26%	--	12
<b>Average</b>			<b>-19.75%</b>	<b>2.61%</b>			<b>-20.16%</b>		
733-20-1	774.833	744.369	-3.93%	0.00%	826.185	770	-6.80%	--	21
733-20-2	918.051	898.418	-2.14%	0.00%	947.452	898.418	-5.18%	--	21
733-20-3	727.102	713.820	-1.83%	0.07%	734.495	721.213	-1.81%	--	21
733-20-4	715.739	659.136	-7.91%	6.70%	739.503	676.499	-8.52%	--	21
733-20-5	612.750	612.750	0.00%	1.00%	650	650	0.00%	19	19
733-20-6	697.678	696.928	-0.11%	0.74%	729.699	702.122	-3.78%	--	21
733-20-7	814.108	800.160	-1.71%	2.74%	830.735	810.53	-2.43%	--	21
733-20-8	859.035	836.672	-2.60%	1.95%	867.379	843.542	-2.75%	--	21
733-20-9	760.872	744.903	-2.10%	1.41%	772.575	744.903	-3.58%	--	21
733-20-10	878.610	869.019	-1.09%	1.17%	885.025	880.379	-0.52%	--	21
<b>Average</b>			<b>-2.34%</b>	<b>1.58%</b>			<b>-3.54%</b>		
733-30-1	774.833	744.369	-3.93%	0.00%	826.185	790	-4.38%	--	31
733-30-2	918.051	898.418	-2.14%	0.00%	947.452	898.418	-5.18%	--	31
733-30-3	713.332	713.332	0.00%	0.00%	730	730	0.00%	29	29
733-30-4	617.767	617.767	0.00%	0.00%	640	640	0.00%	22	22
733-30-5	612.750	612.750	0.00%	1.00%	650	650	0.00%	19	19
733-30-6	697.678	691.814	-0.84%	0.00%	709.699	693.92	-2.22%	--	31

Instance	$C_{CL}$	$C_{TPC}$	$GC_{TPC/CL}$	$GC_{TPC/CP}$	$A_{CL}$	$A_{TPC}$	$GA_{TPC/CL}$	$R_{CL}$	$R_{TPC}$
733-30-7	814.108	800.160	-1.71%	2.74%	820.735	800.53	-2.46%	--	31
733-30-8	859.035	836.672	-2.60%	1.95%	867.379	843.542	-2.75%	--	31
733-30-9	760.872	744.903	-2.10%	1.41%	772.575	744.903	-3.58%	--	31
733-30-10	878.610	869.019	-1.09%	1.17%	885.025	870.379	-1.65%	--	31
<b>Average</b>			<b>-1.44%</b>	<b>0.83%</b>			<b>-2.22%</b>		
733-40-1	757.400	757.400	0.00%	1.75%	800	800	0.00%	32	32
733-40-2	902.749	902.749	0.00%	0.48%	940	940	0.00%	39	39
733-40-3	713.332	713.332	0.00%	0.00%	730	730	0.00%	29	29
733-40-4	617.767	617.767	0.00%	0.00%	640	640	0.00%	22	22
733-40-5	612.750	612.750	0.00%	1.00%	650	650	0.00%	19	19
733-40-6	696.928	696.928	0.00%	0.74%	709.699	709.699	0.00%	39	39
733-40-7	799.651	799.651	0.00%	2.67%	810	810	0.00%	39	39
733-40-8	829.685	829.685	0.00%	1.10%	850	850	0.00%	40	40
733-40-9	741.310	741.310	0.00%	0.92%	770	770	0.00%	40	40
733-40-10	878.074	868.483	-1.09%	1.11%	885.025	870.379	-1.65%	--	41
<b>Average</b>			<b>-0.11%</b>	<b>0.98%</b>			<b>-0.17%</b>		

### 3.6 Chapter summary

This chapter studies a combinatorial auction for truckload transportation service procurement. Two two-phase multi-round combinatorial auction mechanisms with supplementary bundles of lanes generated by the auctioneer and supplementary bids generated by the carriers respectively in the second phase are proposed. The computational results show that the proposed mechanisms can obtain an optimal or a near-optimal allocation with a gap less than 3% for the instances tested. Moreover, the two-phase CA mechanisms can help the auctioneer save procurement costs while improving the social efficiency.

Note that the supplementary bundle generation methods presented in this chapter may not be the only ways to generate supplementary bids. Whether there are other methods to generate supplementary bids and how efficient they are still open questions required to be answered with further investigation. In addition, the problem studied in this chapter can be extended with more complex situations, such as the situation where the carriers participating in CA have to serve their reserved requests, which are defined by pre-existing commitments or contracts with other carriers.

## **4 Column generation algorithm for a bid generation problem**

### **4.1 Introduction**

In truckload transportation, the carriers are the main force in serving transportation requests. Optimizing daily truckload transportation operations of the carriers can help them improve their efficiency facing an ever-increasing competition pressure. For these carriers, they can improve their operation efficiency by acquiring transportation requests which are complementary to their existing ones (Song & Regan, 2003). So, when a shipper procures transportation services from carriers by a combinatorial auction (CA), each carrier must decide which transportation requests to bid to maximize its profit. This problem is known as the bid generation problem.

The bid generation problem (BGP), also referred as bid construction problem or bundle generation problem, is one of the most important decision problems that needs to be solved by each bidder in a combinatorial auction. When participate in a CA for transportation service procurement (TSP), each carrier may bid for multiple combinations of transportation requests provided by the shipper.

In chapter 3, two CA mechanisms for TSP are studied. This chapter is focused on one of the main decision problems of a CA, the bid generation problem, from a carrier's perspective. The BGP considered in Chapter 3 only involves the requests (lanes) provided by the shipper. However, in a general case, before participating in a CA, each carrier may have some pre-exist commitments of serving requests. These commitments may come from long-term contracts between other shippers and the carrier or from former auctions. Therefore, when participating in a new CA, the carrier must consider both pre-exist commitments and the requests that may acquire from this CA. Hereafter, the requests (lanes) to serve defined by the pre-exist commitments of a carrier and the requests offered by a shipper in the considered CA are referred to as reserved lanes and for-bid lanes respectively. The difference between the two types of lanes for a carrier is that it must serve all its reserved lanes whereas it can select some of the for-bid lanes to bid for and to serve. In fact, each carrier takes part in a CA to acquire for-bid lanes that are complementary to its reserved lanes in order to reduce its empty vehicle repositions or to seek more profit. In any case, a carrier will need to reconstruct its vehicle routes to serve both its reserved requests

and the requests it wants to bid for, which makes its BGP and its vehicle routing problem interdependent.

The literatures that study the vehicle routing problem (VRP) of truckload transportation has been reviewed in Chapter 2, section 2.4.1. However, these reviewed studies are focused on the routing and scheduling of truckload vehicles for given requests, request (lane) selection is not considered in their problems. Moreover, the selective vehicle routing problem studied in this chapter involves both reserved lanes that a carrier must serve and for-bid lanes that the carrier chooses to bid for and serve. So, the problem studied in this chapter is different from the ones reviewed.

In the family of VRP, a problem related to the problem studied in this chapter is the team orienteering problem (TOP), which is NP-hard (Chao et al., 1996). In this problem, a fleet of identical vehicles is available to serve a set of customers. The duration of each route is limited/bounded. The objective of the problem is to design a set of routes such that the total profit collected is maximized subject to the maximum duration constraint of each route. For a TOP, due to the duration limit of each route, not all customers can be visited/served, so decisions must be made to select which customers to visit/serve. This selection characteristic also exists in the problem studied in this chapter. TOP attracts attention of scholars in recent years and various algorithms have been developed to solve the problem. For example, Archetti et al. (2009) investigated a capacitated team orienteering and profitable tour problems in a complete undirected graph and proposed exact and heuristic procedures for solving the problem. Poggi et al. (2010) devised an extended formulation for the problem where edges of each route are indexed by the time they are added to the route. A robust Branch-Cut-and-Price algorithm was proposed to solve the problem. Keshtkaran et al. (2016) also proposed a Branch-and-Price approach to find optimal solutions to TOP. El-Hajj et al. (2015) studied a TOP with time windows to maximize the total amount of profit collected from the visited customers. They proposed a column generation-based algorithm to solve the linear relaxation of the problem and used a dynamic programming algorithm to solve the subproblems in order to generate additional columns. Since TOP only has selective customers, it is different from the BGP studied in this chapter.

The team orienteering arc routing problem (TOARP) as an extension of TOP is closer to the studied BGP. In TOARP, there are a set of regular customers and a set of potential customers, which correspond to the reserved lanes and the for-bid lanes in the BGP. Archetti et al. (2013) proposed a formulation for TOARP and presented

some families of valid and facet-inducing inequalities used in the implementation of a branch-and-cut algorithm for the problem. Riera-Ledesma and Salazar-González (2017) proposed a set-partitioning formulation and two column generation algorithms for the problem. However, the studied TOARP only considers the profit collected for serving the selected customers, it does not consider the traveling costs of the routes for serving these customers.

Motivated by Riera-Ledesma and Salazar-González (2017), a column generation algorithm is proposed for solving the BGP studied. The subproblem in the column generation algorithm, which is an elementary shortest path problem, is solved by a dynamic programming based labeling algorithm and by local search respectively.

The rest of the chapter is organized as follows. The description and mathematical formulation of the problem are provided in Section 4.2. In Section 4.3, a column generation algorithm is proposed to solve the linear relaxation of the problem. The procedure of the column generation algorithm, a heuristic to construct an initial solution of the original problem and two methods to solve the subproblem in the column generation algorithm are presented in this section. In Section 4.4, the proposed algorithm is evaluated by comparing it with CPLEX solver that solves a MILP model of the problem on randomly generated instances. Section 4.5 concludes this chapter.

## **4.2 Problem description and formulations**

In the studied bid generation problem, a carrier who participates in a CA for TSP held by a shipper wants to generate a bid to acquire one or multiple truckload requests offered by the shipper. Each truckload request is represented by a lane with an origin and a destination in a transportation network. Before participating in the CA, the carrier has a set of reserved lanes that must be served. In the CA, if the carrier wants to acquire some for-bid lanes, except for selecting the lanes to bid for, it must also reconstruct its vehicle routes to serve its selected for-bid lanes in addition to its reserved lanes.

It is assumed that the carrier has a fleet of vehicles initially located at its vehicle depot with the number of vehicles limited. Each vehicle must leave from and return to its depot before and after serving the lanes assigned to it respectively. Each vehicle can only perform a single route/tour. The service time of each vehicle or equivalently the duration of each route is limited.

### 4.2.1 Mixed-integer linear programming model

The studied BGP, which also considers reserved lanes, is an extension of the BGP involved in Chapter 3. So, this problem can also be formulated as a MILP model. For the convenience to formulate the problem, the following notations are introduced in advance:

---

#### Indices and sets

$N$ : set of all nodes in the transportation network considered

$A$ : set of all possible lanes

$d(d')$ : depot of the carrier

$H$ : set of vehicles of the carrier

$L_r$ : set of reserved lanes

$L_b$ : set of for-bid lanes

$$L_r, L_b \subseteq A$$

#### Parameters:

$c_{i,j}$ : travel cost of lane  $(i, j)$  of the carrier,  $(i, j) \in A$

$t_{i,j}$ : travel time of lane  $(i, j)$  of the carrier,  $(i, j) \in A$

$B$ : maximum travel duration of each vehicle

$R_{i,j}$ : the revenue of serving reserved lane  $(i, j)$  of the carrier,  $(i, j) \in L_r$

$P_{i,j}$ : the outsourcing/procurement price of for-bid lane  $(i, j)$  given by the auctioneer/shipper,  $(i, j) \in L_b$

#### Decision variables:

$$u_{i,j}^h = \begin{cases} 1, & \text{if reserved lane } (i, j) \text{ is served by vehicle } h \\ 0, & \text{otherwise} \end{cases}; (i, j) \in L_r, h \in H$$

$$v_{i,j}^h = \begin{cases} 1, & \text{if for-bid lane } (i, j) \text{ is chosen and served by vehicle } h \\ 0, & \text{otherwise} \end{cases}; (i, j) \in L_b, h \in H$$

$$x_{i,j}^h = \begin{cases} 1, & \text{if vehicle } h \text{ travel through arc } (i, j) \\ 0, & \text{otherwise} \end{cases}; (i, j) \in A, h \in H$$

$S_i^h$ , the time at which vehicle  $h$  leaves node  $i$ ;  $i \in N, h \in H$ ;

---



Then the studied BGP can be formulated as:

Model *BGP*

$$\text{Max} \sum_{h \in H} \left( \sum_{(i,j) \in L_r} u_{i,j}^h R_{i,j} + \sum_{(i,j) \in L_b} v_{i,j}^h P_{i,j} - \sum_{(i,j) \in A} c_{i,j} x_{i,j}^h \right)$$

s.t.

$$\sum_{j \in N} x_{i,j}^h = \sum_{j \in N} x_{j,i}^h, \quad i \in N \setminus \{d, d'\}, \quad h \in H \quad (4-1)$$

$$\sum_{j \in N} x_{i,j}^h \leq 1, \quad i \in N, \quad h \in H \quad (4-2)$$

$$\sum_{i \in N \setminus d} x_{d,i}^h = 1, \quad h \in H \quad (4-3)$$

$$\sum_{j \in N \setminus d'} x_{j,d'}^h = 1, \quad h \in H \quad (4-4)$$

$$x_{i,j}^h \geq u_{i,j}^h + v_{i,j}^h, \quad (i,j) \in A, \quad h \in H \quad (4-5)$$

$$\sum_{h \in H} u_{i,j}^h = 1; \quad (i,j) \in L_r \quad (4-6)$$

$$\sum_{h \in H} v_{i,j}^h \leq 1, \quad (i,j) \in L_b \quad (4-7)$$

$$\sum_{(i,j) \in A} x_{i,j}^h t_{i,j} \leq B, \quad h \in H \quad (4-8)$$

$$S_d^h = 0, \quad h \in H \quad (4-9)$$

$$S_j^h \geq S_i^h + x_{i,j}^h t_{i,j} - B(1 - x_{i,j}^h), \quad i, j \in N, \quad h \in H \quad (4-10)$$

$$u_{i,j}^h = 0; \quad (i,j) \in A \setminus L_r, \quad h \in H \quad (4-11)$$

$$v_{i,j}^h = 0, \quad (i,j) \in A \setminus L_b, \quad h \in H \quad (4-12)$$

The objective function is to maximize the net profit of the carrier, which is the difference between the total revenue to serve all reserved lanes and selected for-bid lanes and the total travel cost. Constraint (4-1) guarantees the vehicle flow equilibrium at each node except for the depot node of the carrier since the depot node is duplicated as origin node and destination node for all routes respectively. Constraint (4-2) indicates that for any vehicle, if it leaves a node, the next node it can visit is unique. Constraints (4-3) and (4-4) ensure that all vehicles leave from and return to its depot after completing the service. Constraint (4-5) ensures that each lane with a transportation request will be served, no matter it is a reserved lane or a for-bid lane.

Constraint (4-6) indicates that for the carrier, each of its reserved lanes is served exactly once by a unique vehicle. Constraint (4-7) guarantees that each for-bid lane is served at most once by a vehicle of the carrier. Constraint (4-8) limits the travel duration of each vehicle. Constraint (4-9) sets the departure time of each vehicle from its depot as 0. Constraint (4-10) ensures that if a vehicle travels through lane  $(i, j)$ , the time difference between the departure time at node  $j$  and that at node  $i$  is at least the travel time of the lane. This constraint eliminates all sub-tours. Constraint (4-11) and constraint (4-12) define the value of binary variable  $u_{i,j}^h$  and  $v_{i,j}^h$  respectively according to whether its corresponding lane is a reserved lane or a for-bid lane. On the one hand, if  $(i, j)$  is not a reserved lane,  $u_{i,j}^h = 0$ . On the other hand, if  $(i, j)$  is not a for-bid lane,  $v_{i,j}^h = 0$ .

#### 4.2.2 Set partition model

The linear relaxation of the MILP model for the studied BGP is very weak/loose because of constraints (4-8) and (4-10). The conventional branch-and-bound approach can only solve the MILP model with very small size, which is not practical in reality. Through the Dantzig-Wolfe decomposition (Dantzig & Wolfe, 1960), a set partition formulation of the considered BGP can be obtained with a much tighter linear relaxation. The new model can be formulated with the following notations defined:

---

##### Sets and indices:

$R$ , set of all possible routes

$A$ , set of all lanes

$A_r$ , set of lanes included in route  $r$ ,  $r \in R$

##### Parameters:

$$a_{l,r} = \begin{cases} 1, & \text{if lane } l \text{ is in route } r \\ 0, & \text{otherwise} \end{cases}; l \in A, r \in R$$

$C_l$ , the cost of serving/passing through lane  $l$ ;  $l \in A$

$P_l$ , the revenue of serving lane  $l$ ;  $l \in A$

##### Decision variables:

$$x_r = \begin{cases} 1, & \text{if route } r \text{ is included in the optimal solution} \\ 0, & \text{otherwise} \end{cases}; r \in R$$

Then the studied BGP can be formulated with the following set partition model:

Model *BGP-SP*

$$Max \sum_{r \in R} \sum_{l \in A_r} (P_l - C_l) a_{l,r} x_r$$

s.t.

$$\sum_{r \in R} a_{l,r} x_r = 1; l \in L_r \quad (4-13)$$

$$\sum_{r \in R} a_{l,r} x_r \leq 1; l \in L_b \quad (4-14)$$

$$\sum_{r \in R} x_r \leq H \quad (4-15)$$

$$x_r \in \{0, 1\}, r \in R \quad (4-16)$$

The objective function is still to maximize the net profit of the carrier. The net profit is the difference between the total revenue and the total cost of serving all the lanes by the routes. Constraint (4-13) corresponds to constraint (4-6) and ensures that each reserved lane is served only once, whereas constraint (4-14) corresponds to constraint (4-7) and ensures that any for-bid lane can be served at most once by the carrier. Constraint (4-15) guarantees that the number of vehicles used does not exceed its available number. Constraint (4-16) defines the value range of each binary variable  $x_r$ .

### 4.3 Column generation algorithm

In the set partition model, the set  $R$  contains all possible routes respecting the maximum travel duration constraint. However, considering all possible routes in solving the model is computationally unaffordable for a practical instance of the model. To overcome this difficulty, a column generation algorithm can be applied to solve the model, which is an iterative procedure considering the routes in the model implicitly and progressively.

#### 4.3.1 Procedure of the column generation algorithm

Column generation is an efficient algorithm for solving linear programs with a large number of columns/variables. The main advantage of column generation is that not all columns/variables need to be enumerated/considered in solving a linear programming model. To implement a column generation algorithm, a restricted master problem and a subproblem must be formulated. The restricted master problem (RMP)

is the original problem with only a subset of variables considered. The solution of the RMP is a feasible solution to the original problem. The subproblem (SP) is a problem used to identify a column to be added into the RMP in each iteration of the column generation algorithm. The new column is found by solving the subproblem to find a column with positive reduced cost (if the original problem is a maximization problem) with respect to the optimal values of the dual variables of the RMP (or the optimal solution of the dual model of the RMP). Generally, the column that maximizes the reduced cost is added to the restricted master problem (for a maximization original problem). This means adding this column can improve the current solution of the original problem to the greatest extent.

The column generation algorithm deals with the linear relaxation model of the set partition model *BGP-SP* of the studied problem, in which all binary variables  $x_r$  are relaxed to real variables.

#### 4.3.1.1 Restricted master problem and its dual model

Let  $R_0$  denote a subset of  $R$  considered initially in solving the set partition model by column generation, then the restricted master problem of the model can be formulated as:

Model *RMP*

$$Max \sum_{r \in R_0} \sum_{l \in A} (P_l - C_l) a_{l,r} x_r$$

s.t.

$$\sum_{r \in R_0} a_{l,r} x_r = 1; l \in L_r \quad (4-17)$$

$$\sum_{r \in R_0} a_{l,r} x_r \leq 1; l \in L_b \quad (4-18)$$

$$\sum_{r \in R_0} x_r \leq H \quad (4-19)$$

$$0 \leq x_r \leq 1, r \in R_0 \quad (4-20)$$

Constraint (4-17) - (4-20) play the same roles as constraint (4-13) - (4-16). Note that in constraint (4-20) the value range of variable  $x_r$  is changed after linear relaxation compared to constraint (4-16).

The dual model of the restricted master problem can be formulated as follows:

Model *D-RMP*

$$\text{Min} \sum_{l \in A} \lambda_l + H \mu$$

s.t.

$$\sum_{l \in A_r} a_{l,r} \lambda_l + \mu \geq \sum_{l \in A_r} (P_l - C_l) a_{l,r}; \quad r \in R \quad (4-21)$$

$$\lambda_l \in \mathbb{R}; \quad l \in L_r \quad (4-22)$$

$$\lambda_l \geq 0; \quad l \in L_b \quad (4-23)$$

$$\mu \geq 0 \quad (4-24)$$

In the dual model, variable  $\lambda_l$  is the dual variable associated with constraint (4-17) and (4-18). When lane  $l$  is a reserved lane, i.e.,  $l \in L_r$ , then the dual variable  $\lambda_l$  can take any value as indicated by constraint (4-22). On the other hand, when lane  $l$  is a for-bid lane, i.e.,  $l \in L_b$ , the dual variable  $\lambda_l$  must take a nonnegative value as indicated by constraint (4-23). Variable  $\mu$  is the dual variable associated with constraint (4-19), with its value range indicated by constraint (4-24).

As introduced at the beginning of this section, the subproblem of the column generation algorithm aims at finding a column with the largest reduced cost (for a maximization original problem). The reduced cost coefficient of each column can be obtained with the optimal values of the dual variables of the restricted master problem. In specific, let  $c_j$  denotes the coefficient of the  $j$ -th column in the objective function of the set participation model,  $\bar{c}_j$  denotes the reduced cost coefficient of this column in the model, then

$$\bar{c}_j = c_j - \lambda^T a_j \quad (4-25)$$

where  $a_j$  is the  $j$ -th column in the constraint matrix of the model and  $\lambda = (\lambda_l, l \in L_r \cup L_b)$  is the vector of the optimal values of the dual variables of model *D-RMP*. Therefore, the dual model of the restricted master problem must be solved before solving the subproblem.

With the given values of the dual variables, the reduced cost coefficient  $\bar{c}_j$  can be calculated as

$$\sum_{l \in A_r} (P_l - C_l) a_{l,r} - \left( \sum_{l \in A_r} a_{l,r} \lambda_l + \mu \right)$$

#### 4.3.1.2 Subproblem

Since our considered BGP is a maximization problem, the subproblem of the column generation algorithm is to find a new route with a positive reduced cost, that is, to find a new route such that:

$$\sum_{l \in A_r} (P_l - C_l) a_{l,r} - \left( \sum_{l \in A_r} a_{l,r} \lambda_l + \mu \right) \geq 0 \quad (4-26)$$

In order to conform to the usual expression of column generation whose subproblem is to find a column with negative reduced cost, here multiply both sides of the inequality (4-26) by -1 to obtain the inequality (4-27). Then, the subproblem becomes a problem to find a route  $x_r \in R \setminus R_0$  with negative reduced cost such that

$$\sum_{l \in A_r} a_{l,r} \lambda_l + \mu - \sum_{l \in A} (P_l - C_l) a_{l,r} \leq 0 \quad (4-27)$$

Generally, the column to be added in the restricted master problem is the one that can best improve the objective value of the original problem. Then the subproblem to find a new column, which corresponds to a new route in our considered BGP, can be viewed as an elementary shortest path problem with resource constraint (ESPPRC) which can be formulated as:

Model *ESPPRC*

$$\text{Min} \sum_{(i,j) \in A} \bar{c}_{i,j} x_{i,j}$$

s.t.

constraint (4-1) – (4-12) without index  $h$

where the distance matrix  $\bar{c}_{i,j}$  is defined as

$$\bar{c}_{i,j} = \begin{cases} \lambda_l - (R_{i,j} - c_{i,j}), & (i,j) \in L_r \\ \lambda_l - (P_{i,j} - c_{i,j}), & (i,j) \in L_b \\ c_{i,j}, & (i,j) \in A \setminus \{L_r \cup L_b\} \end{cases}$$

The procedure of the column generation algorithm for solving the studied BGP can be summarized as follows.

- (1) Generate an initial solution of the BGP with a set  $R_0$  of routes (initial columns for the *RMP*),  $R_0 \subset R$ .
- (2) Solve the dual model of the restricted master problem, i.e., Model *D-RMP*, and obtain the optimal values of all dual variables.
- (3) For the given values of the dual variables, solve the subproblem to find the route with the smallest reduced cost.
- (4) Check if the route found has a negative reduced cost, if it has, add the column corresponding to the route to the restricted master problem and go to step (2). Otherwise, the algorithm stops with the solution of the final restricted master problem with variable range constraints (4-20) replaced by (4-16), which is an optimal or near-optimal solution of the original problem.

#### **4.3.2 Construction of an initial solution of the original problem**

The BGP studied considers two types of lanes with transportation requests, the reserved lanes and the for-bid lanes. Since the reserved lanes must be served, the simplest way to obtain an initial solution of the problem is to solve a simplified problem which only considers the reserved lanes. The solution to this problem must be a feasible solution of the original problem. However, construct an initial solution in this way may not be very efficient if the proportion of for-bid lanes in all lanes is large.

In our proposed column generation algorithm, a greedy insertion heuristic is designed to generate the initial solution. This heuristic constructs routes one by one, it first tries to insert/serve all reserved lanes and then tries to insert profitable for-bid lanes as many as possible until the number of vehicles used reaches its maximum number, i.e., the number of available vehicles. When constructing a route, the heuristic first selects a seed lane to insert into an empty route containing only the vehicle depot node. This seed lane is the farthest lane among all possible lanes in terms of the duration of the route that only serves the lane. For the current route to construct with the seed lane already inserted, the heuristic tries to insert the lane with maximal net profit increase among all possible lanes to the route while respecting its maximum duration constraint in each insertion. Let  $\Omega_r$  and  $\Omega_b$  be the sets of reserved and for-bid lanes to be inserted respectively,  $D_r$  be the travel duration of route  $r$ ,  $R$  be the set of routes constructed,  $|R|$  is the number of routes in  $R$ , then the procedure of the

heuristic is presented as follows:

---

**Greedy insertion heuristic**

---

**{Initialization}**

1  $\Omega_r = L_r, \Omega_b = L_b$

2  $R = \emptyset$

**{Create routes and insert the reserved lanes}**

3 **while**  $\Omega_r \neq \emptyset$  and  $|R| < H$  **do**

4 select a seed reserved lane  $l_r^s = (i, j) \in \Omega_r$  with maximum value of  $t_{d,i} + t_{i,j} + t_{j,d}$ , among all remaining reserved lanes, insert it to an empty new route  $r$  and update  $D_r$

5  $R = R \cup \{r\}$

6  $\Omega_r = \Omega_r \setminus l_r^s$

7 **while**  $D_r < B$  **do**

8 insert a reserved lane  $l_r \in \Omega_r$  with maximum net profit increase among all remaining reserved lanes to route  $r$  such that the travel duration of the route after this insertion respects the constraint  $D_r \leq B$

9  $\Omega_r = \Omega_r \setminus l_r$

**{Insert for-bid lanes into the existing routes}**

10 **while**  $\Omega_b \neq \emptyset$  **do**

11 insert a for-bid lane  $l_b \in \Omega_b$  into an existing route  $r \in R$  with  $D_r < B$  such that this insertion maximizes the net profit increase among all possible insertions of this type, and update  $D_r$  of the corresponding route

12  $\Omega_b = \Omega_b \setminus l_b$

13 **until** no remaining for-bid lane can be inserted into an existing route

**{Create routes and insert the remaining for-bid lanes}**

14 **while**  $\Omega_b \neq \emptyset$  and  $|R| < H$  **do**

15 select a seed for-bid lane  $l_b^s = (i, j) \in \Omega_b$  with maximum value of  $t_{d,i} + t_{i,j} + t_{j,d}$ , among all remaining for-bid lanes, insert it to an empty new route  $r$  and update  $D_r$

16 **if** the net profit of the new route  $r$  is positive

17  $R = R \cup \{r\}$

18  $\Omega_b = \Omega_b \setminus l_b^s$

19 **while**  $D_r < B$  **do**

20 insert a for-bid lane  $l_b \in \Omega_b$  with maximum net profit increase among all remaining for-bid lanes to route  $r$  such that the travel duration of the route after this insertion respects the constraint  $D_r \leq B$

21  $\Omega_b = \Omega_b \setminus l_b$

**{Output the initial solution}**

22 output each route constructed

---



### 4.3.3 Methods for solving the subproblem

Efficiently solving the subproblem is important for the column generation algorithm because most of its computation time is spent on the resolution of the subproblem. The most straightforward way to solve the subproblem is to solve its MILP model by a commercial solver like CPLEX solver. However, this method may not be the most efficient one. In this section, two methods to solve the subproblem are proposed and investigated, one is a dynamic programming based labeling algorithm and the other is a local search algorithm.

#### 4.3.3.1 Dynamic programming based labeling algorithm

Dynamic programming is a mathematical optimization method first proposed by Richard Bellman in the 1950s, this method is often used for multi-stage decision problems, it is widely applied in many fields such as engineering, production and economics. The labeling algorithm, as one type of dynamic programming algorithm, is typically used to solve elementary shortest path problems with resource constraints (ESPPRC) arising in using column generation to solve various vehicle routing problems (Feillet et al., 2004; Gschwind et al., 2018; Ropke & Cordeau, 2009; Vitale & Dondo, 2020). Irnich and Desaulniers (2005) provides an overview of methods for solving the ESPPRCs.

In the ESPPRC of the column generation proposed for the studied BGP, a route with lowest cost and respecting the maximum duration constraint needs to be found. This route must start and end at the vehicle depot of the carrier and serve some of reserved requests (lanes) and for-bid requests (lanes).

In this labeling algorithm to solve the ESPPRC, a label  $L_i = \{S_i, d_i, c_i, U_i, n_i\}$  is defined with the ordered list  $S_i$  of visited requests, the departure time  $d_i$  after serving the current request  $i$ , the accumulated cost  $c_i$ , the set of unreachable requests  $U_i$  and the number of unreachable requests  $n_i$ . Here, a request is considered unreachable if it has been already served in the partial route defined by the label or serving the request will cause the violation of the maximum duration constraint. The label will be extended from  $L_i = \{S_i, d_i, c_i, U_i, n_i\}$  to  $L_j = \{S_j, d_j, c_j, U_j, n_j\}$  if request  $j$  is served next in the route. Before adding request  $j$ , it is firstly checked if it is an unreachable request. If it can be added to the route, let  $i^+$  be the origin node and  $i^-$  be the destination node of request  $i$ , then

$$S_j = S_i \leftarrow j \quad (4-28)$$

$$d_j = d_i + t_{i^-,j^+} + t_{j^+,j^-} \quad (4-29)$$

$$c_j = c_i + c_{i^-,j^+} + c_{j^+,j^-} \quad (4-30)$$

Note if request  $j$  is the first request considered after leaving the vehicle depot, then in the new label  $L_j$ ,  $d_j$  and  $c_j$  are set to  $d_j = t_{d,j^+} + t_{j^+,j^-}$  and  $c_j = c_{d,j^+} + c_{j^+,j^-}$ , respectively. Finally, if the partial route ends at the depot node, i.e., the partial route becomes a complete route, then in the new label defining the route, the list of visited requests, the duration and the cost of the route are set to  $S_i$ ,  $d_i + t_{i^-,d'}$ , and  $c_i + c_{i^-,d'}$ , respectively, where request  $i$  is the last request served in the route.

After updating  $S_j$ ,  $d_j$  and  $c_j$  for the new label, its  $U_j$  and  $n_j$  will also be updated after checking the origin node of each remaining request and the maximum duration constraint.

To limit the number of new labels generated in the labeling algorithm, a dominance rule is applied to eliminate all dominated labels. For two labels  $L_j^1$  and  $L_j^2$  associated with request  $j$  (i.e., their last request served is request  $j$ ), label  $L_j^1$  dominates label  $L_j^2$  if

$$d_j^1 \leq d_j^2, c_j^1 \leq c_j^2, U_j^1 \subseteq U_j^2, n_j^1 \leq n_j^2 \quad (4-31)$$

Let  $\Lambda_i$  denote the list of labels associated with request  $i$ ,  $E$  denote the requests that need to be examined, the procedure of the labeling algorithm can be described as follows:

---

**Labeling algorithm for ESPPRC**

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- {Initialization}**
- 1  $\Lambda_D = \{\emptyset, 0, 0, \emptyset, 0\}$
  - 2 **for all**  $i \in L_r \cup L_b$
  - 3      $\Lambda_i = \emptyset$
  - 4  $E = L_r \cup L_b$
- {Main loop}**
- 5 **while**  $E \neq \emptyset$  **do**
  - 6     **for all**  $j \in E \setminus U_i$
  - 7         extend label  $L_i$  to  $L_j$

---

```

8      check the dominance of the extended label
9      if  $L_j$  is not dominated by any existing label
10      $\Lambda_j = \Lambda_j \cup \{L_j\}$ 
11      $E = E \setminus \{i\}$ 
12     if  $\Lambda_j$  is changed
13      $E = E \cup \{j\}$ 
      {Output the results}
14     output the route with minimum reduced cost

```

---

#### 4.3.3.2 Local search algorithm

The labeling algorithm presented in the last subsection is time consuming when the number of requests is large and the maximum duration of each route is large, so it is not suitable for large instances of the BGP considered. Heuristic methods are usually proposed to approximately solve the ESPPRCs appeared in column generation algorithms for various vehicle routing problems. One heuristic method is, instead of solving an elementary shortest path problem, a shortest path problem that allows some nodes visited by more than one time in a partial path (route) is considered, but the relaxation of the constraint that each node is visited by a partial path (route) at most once will degrade the lower bound of the corresponding set partition model found by column generation. For this reason, a local search algorithm is proposed to solve the subproblem.

In the column generation algorithm, after solving the dual problem of the restricted master problem, the reduced cost of each route in the route (column) pool can be calculated. The local search algorithm tries to improve some routes with zero reduced cost in the route pool such that routes with negative reduced cost can be found and enter the column pool. This algorithm applies the following three local search operators:

- (1) Remove a request (lane). For a given route, this operator removes a request whose removal will maximally reduce the reduced cost of the route among all removable requests.
- (2) Insert a request (lane). For a given route, this operator inserts a request whose insertion will maximally reduce the reduced cost of the route among all insert-able requests and reconstructs the route by inserting the request into its best position that minimizes the reduced cost. Note that in the ESPPRC considered, some lanes are associated with a negative cost (distance), so the insertion of a request (lane) may reduce the reduced cost of the route.
- (3) Remove and insert a request (lane). For a given route, this operator first

removes a request from the route and then reinsert this request (in another position) or insert another request into the route. The combination of the request to remove and the request to insert is chosen such that the reduced cost of the route is reduced at maximum after this request removal/insertion operation.

There may be many routes with zero reduced cost to be improved in an iteration of the column generation algorithm, so in contrast to the labeling algorithm who identifies and adds a single route (column) with negative reduced cost to the restricted master problem in each iteration of the algorithm, the local search algorithm tries to improve and add multiple routes to the restricted master problem in each iteration. For each route selected to improve, the local search improving process iterates until the reduced cost of the route cannot be further reduced.

Let  $R$  be the set of routes in the route pool of the restricted master problem,  $R^*$  be the set of routes to be improved,  $V_r$  be the set of requests served by route  $r$  for any  $r \in R$ . The procedure of the local search algorithm can be described as follows:

---

#### Local search algorithm

---

**{Find the routes to be improved}**

- 1 **for all**  $r \in R$
- 2     calculate the reduced cost  $\bar{c}_r$  of each route  $r$  based on the dual variables of the restricted master problem
- 3      $R^* = \{r \mid r \in R \text{ and } \bar{c}_r = 0\}$
- {Main loop}**
- 4 **for all**  $r \in R^*$
- 5     **do**
- 6          $V_r :=$  the set of requests served by route  $r$
- 7         **(Operator 1)**  
Find the best  $l \in V_r$  whose removal from route  $r$  will reduce the reduced cost of the route at maximum with reduced cost reduction  $\Delta\bar{c}_r$
- 8         **if**  $\Delta\bar{c}_r > 0$
- 9             remove lane  $l$  from route  $r$ ,  $V_r = V_r \setminus l$
- 10         **(Operator 2)**  
Find the best request  $l \notin V_r$  whose insertion into route  $r$  will reduce the reduced cost of the route at maximum with reduced cost reduction  $\Delta\bar{c}_r$
- 11         **if**  $\Delta\bar{c}_r > 0$
- 12             insert lane  $l$  into route  $r$ ,  $V_r = V_r \cup \{l\}$
- 13         **(Operator 3)**  
Find the best combination of  $l_1 \in V_r$  and  $l_2 \notin V_r \setminus \{l_1\}$  such that removing lane  $l_1$  from route  $r$  and then inserting lane  $l_2$  into route  $r$  will

---

```

    reduce the reduced cost of the route at maximum with reduced cost
    reduction  $\Delta\bar{c}_r$ 
14   if  $\Delta\bar{c}_r > 0$ 
15       remove lane  $l_1$  from route  $r$  and then insert  $l_2$  into the route,
         $V_r = V_r \cup \{l_2\} \setminus l_1$ 
16   until the reduced cost of route  $r$  cannot be reduced anymore
    {Output the results}
17   output the improved routes and their reduced costs

```

---

Note that there may be a large number of routes with zero reduced cost that can be improved in the route pool, so in implementation, the number of routes improved by the local search algorithm in each iteration of column generation is limited to a reasonable number.

After the iterative procedure of the column generation algorithm is terminated, no matter which method is used to solve the subproblem, the final restricted master problem with all the routes added and the variable range constraints (4-20) replaced by (4-16) is solved. The solution of the problem provides an optimal or near-optimal solution of the original bid generation problem.

## 4.4 Computational experiments

In this section, the efficiency of the proposed column generation algorithm is evaluated by numerical experiments on randomly generated instances. All the algorithms involved are coded in C++ and all mixed-integer linear programs and linear programs involved are solved by CPLEX solver. The objective value of the MILP model *BGP* (the next profit of the carrier) obtained by CPLEX solver are used as a benchmark for evaluating the efficiency of the proposed algorithm. All the tests are conducted on a PC with Intel® Core™ i7-8750H CPU and 16 GB RAM. The version of CPLEX is 12.10.0.0 for 64-bit Windows.

### 4.4.1 Parameter setting

The parameters used to generate the instances in the experiments are given in Table 4-1. For simplicity, both the travel time between the origin and the destination of each lane  $(i, j)$  and the cost of travelling through the lane  $(i, j)$  are set to its Euclidean distance.

Table 4-1 Parameter values for the generation of the instances

Parameter	Value
Proportion of reserved lanes in all lanes with request	50%
Proportion of for-bid lanes in all lanes with request	50%

Parameter	Value
Coordinates $(x_0, y_0)$ of the vehicle depot of the carrier	$U[0, 100] \times [0, 100]$
Coordinates $(x_i, y_i)$ of each node $i \in N$	$U[0, 100] \times [0, 100]$
$t_{i,j}, c_{i,j}$	$\sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$
Revenue of a request (lane) $(i, j)$ with request	$2 * c_{i,j}$
Maximum duration $B$ of each route	480

#### 4.4.2 Experiments with subproblem solved by labeling algorithm

Firstly, tests on the column generation algorithm with the subproblem solved by the labeling algorithm are conducted. In this group of tests, 2 sets of instances with the number of nodes  $N = 10$  and  $20$  are tested respectively. The total number of requests is also set as  $10$  and  $20$  respectively. The number of vehicles is respectively set as  $H = 2$  and  $4$ . For this group of tests, each instance is identified by its number of nodes, total number of requests, number of vehicles, and its serial number. For example, instance 10-10-2-1 represents the first instance with 10 nodes in the transportation network, 10 lanes with request, including 5 reserved lanes and 5 for-bid lanes, and the number of vehicles available for serving these requests is 2.

To evaluate the efficiency of the labeling algorithm for solving the subproblem, the results obtained by the column generation algorithm with the results obtained by directly solving the model  $BGP$  using CPLEX solver are compared. In addition, these results are also compared with the results obtained by the algorithm with the subproblem formulated as the MILP model  $ESPPRC$  and solved by CPLEX solver. The comparison results are showed in Table 4-2, where  $P$  denotes the net profit of the carrier obtained by each method, and  $T$  denotes the CPU time for obtaining a solution by each method. The subscript in  $P$  and  $T$  indicates the method used to solve the bid generation problem or the method used to solve the subproblem of the column generation algorithm, where “espprc” indicates that the subproblem is formulated as the MILP model  $ESPPRC$  and solved by CPLEX solver, “dyla” indicates that the subproblem is solved by using the dynamic programming based labeling algorithm. The Gap for each instance in the table is calculated by  $(P_{dpla} - P_{cplex}) / P_{cplex}$ . The time limit of CPLEX solver for solving each instance is set as 3600 seconds,  $P_{cplex}$  is the objective value of the MILP model  $BGP$  obtained by CPLEX solver when the time limit is reached. If CPLEX solver cannot obtain a feasible solution within the time limit, then there is no objective value of model  $BGP$  given in the table, this case is marked by two hyphens.

Since the column generation algorithm solves the dual model  $D-RMP$  of the

linear relaxation of the restricted master problem in each iteration, the optimal objective value of *D-RMP* provides an upper bound for the optimal objective value of the original bid generation problem which is a maximization problem. On the other hand, the feasible solution of the original problem finally obtained by the algorithm provides a lower bound for the optimal objective value. In Table 4-2, the upper bound  $D_{dpla}$  of each instance is also given, as well as its relative gap  $Gap_{D/P}$  with the lower bound  $P_{dpla}$ . This gap is calculated by  $(D_{dpla} - P_{dpla}) / D_{dpla}$ .

The results of this group given in Table 4-2 show that both solving the model *ESPPRC* of the subproblem by CPLEX solver and using the labeling algorithm can obtain an optimal or near optimal solution for the instances of small size with  $N = 10$  in very short time. The upper bound obtained by the column generation algorithm is actually very close to the objective value obtained by solving the MILP model of the original problem for each instance. When the problem size increases, using CPLEX to directly solve the MILP model *BGP* becomes very time-consuming, so does using CPLEX to solve the model *ESPPRC*. The column generation algorithm with the subproblem solved by the labeling algorithm can still obtain a solution in a reasonable time for the instances with  $N = 20$ , but compared with the solutions obtained by directly solving the model *BGP* using CPLEX, the gap becomes bigger.

Note that this chapter implement a column generation algorithm rather than branch and price in the experiments. If branch and price is implemented, optimal solution can be obtained for each instance if the computation time is not limited.

Table 4-2 Results with exact algorithm to solve the subproblem

Instance	$P_{cplex}$	$T_{cplex}(s)$	$P_{espprc}$	$T_{espprc}(s)$	$P_{dpla}$	$D_{dpla}$	$T_{dpla}(s)$	$Gap_{dpla/cplex}$	$Gap_{D/P}$
10-10-2-1	234.028	0.642	210.506	6.293	210.506	240.275	2.022	10.05%	12.39%
10-10-2-2	419.820	0.821	419.820	3.015	419.192	426.241	0.386	0.15%	1.65%
10-10-2-3	371.336	0.494	371.336	6.560	371.336	371.336	0.365	0.00%	0.00%
10-10-2-4	347.757	0.273	347.757	3.494	347.757	347.757	0.618	0.00%	0.00%
10-10-2-5	278.723	3.539	278.723	33.48	278.723	284.224	1.412	0.00%	1.94%
10-10-2-6	302.975	3.047	227.327	5.157	227.327	327.124	3.963	24.97%	30.51%
10-10-2-7	160.698	2.662	160.698	10.40	160.698	161.508	9.228	0.00%	0.50%
10-10-2-8	154.716	0.553	141.845	3.865	141.845	158.035	3.605	8.32%	10.24%
10-10-2-9	361.474	0.572	325.912	4.986	325.912	361.613	0.677	9.84%	9.87%
10-10-2-10	336.244	1.327	330.531	9.843	330.531	340.160	0.297	1.70%	2.83%
<b>Average</b>		<b>1.393</b>		<b>8.709</b>			<b>2.257</b>	<b>5.50%</b>	<b>6.99%</b>
20-20-4-1	874.862	3600	--		719.981	897.37	20.70	17.70%	19.77%
20-20-4-2	508.519	3600	--		504.7	514.846	21.04	0.75%	1.97%
20-20-4-3	679.000	3600	--		665.967	684.351	60.12	1.92%	2.69%
20-20-4-4	614.324	3600	--		544.942	624.002	93.62	11.29%	12.67%

Instance	$P_{\text{cplex}}$	$T_{\text{cplex}}(\text{s})$	$P_{\text{espprc}}$	$T_{\text{espprc}}(\text{s})$	$P_{\text{dpla}}$	$D_{\text{dpla}}$	$T_{\text{dpla}}(\text{s})$	$\text{Gap}_{\text{dpla/cplex}}$	$\text{Gap}_{D/P}$
20-20-4-5	578.069	3600	--		577.207	584.296	293.6	0.15%	1.21%
20-20-4-6	772.232	3600	--		600.718	775.209	684.3	22.21%	22.51%
20-20-4-7	593.113	3600	--		571.725	593.113	398.2	3.61%	3.61%
20-20-4-8	656.931	3600	--		526.171	673.49	88.45	19.90%	21.87%
20-20-4-9	663.387	3600	--		626.954	676.796	77.08	5.49%	7.36%
20-20-4-10	367.789	3600	--		372.659	404.303	108.4	-1.32%	7.83%
<b>Average</b>		<b>3600</b>					<b>184.6</b>	<b>8.17%</b>	<b>10.15%</b>

#### 4.4.3 Experiments with subproblem solved by local search algorithm

Secondly, tests to evaluate the efficiency of the column generation algorithm with the subproblem solved by the proposed local search algorithm are conducted. In this group of tests, five sets of instances with the number of nodes  $N = 10, 20, 30, 40$  and  $50$  respectively are tested. The total number of requests is set accordingly as the number of nodes for the five sets while the number of vehicles are set as  $H = 2, 4, 6, 8$  and  $10$ , respectively.

For this group of tests, to enlarge the search space of the local search algorithm, the condition for improving a route by local search is changed/relaxed from  $c_r = 0$  to  $c_r \leq 1$ , so more routes can be improved. In addition, the number of routes to be improved in each iteration of the column generation algorithm is limited by 100.

Table 4-3 shows the net profit  $P_{\text{ls}}$  of the carrier obtained by the column generation algorithm with local search and its CPU time for each instance as well as the relative gap between  $P_{\text{ls}}$  and the net profit  $P_{\text{cplex}}$  of the carrier obtained by solving the MILP model *BGP* using CPLEX. It can be observed that the average gap is ranged from 2 to 5%. In addition, the upper bound  $D_{\text{ls}}$  of each instance obtained by the column generation algorithm with subproblem solved by local search and its relative gap with the lower bound  $P_{\text{ls}}$  are also presented in this table.

Using the column generation algorithm with local search to solve the studied bid generation problem can greatly reduce computation time compared with CPLEX solver, its advantage over CPLEX solver in computation time is very evident. The CPLEX solver cannot obtain a feasible solution for some instances with 30 nodes and 30 requests after an hour of running. When the number of nodes and requests exceeds 40, no feasible solution is obtained by CPLEX solver after an hour of running for any instance. In contrast, the column generation algorithm with local search can solve all the instances tested within 30 seconds. Therefore, this algorithm can solve large instances of the considered BGP within a reasonable time.

By comparing the results of all instances obtained by the column generation



algorithm with labeling algorithm and that with local search for the subproblem in Table 4-2 and Table 4-3, we find that if the subproblem is solved optimally by the labeling algorithm, the column generation algorithm can obtain an upper bound better than or the same as the upper bound obtained by the same column generation algorithm with the subproblem solved near-optimally by local search. However, the net profit of the carrier (a lower bound for the maximization bid generation problem considered) obtained by the column generation algorithm with local search is better than the net profit obtained by the column generation algorithm with labeling algorithm for some instances, this may be because more columns are added to the restricted master problem by the local search algorithm than by the labeling algorithm. As a result, when solving the final restricted master problem with all columns (routes) added after the termination of the column generation algorithm, that with more columns added may obtain a better solution for the original problem. This is one advantage of our local search based column generation algorithm.

Table 4-3 Results with local search algorithm to solve the subproblem

<b>Instance</b>	$P_{cplex}$	$T_{cplex}(s)$	$P_{ls}$	$D_{ls}$	$T_{ls}(s)$	$Gap_{la/cplex}$	$Gap_{D/P}$
10-10-2-1	234.028	0.642	233.318	239.579	2.505	0.30%	2.61%
10-10-2-2	419.820	0.821	419.820	426.241	0.616	0.00%	1.51%
10-10-2-3	371.336	0.494	371.336	371.336	0.271	0.00%	0.00%
10-10-2-4	347.757	0.273	347.757	347.757	2.578	0.00%	0.00%
10-10-2-5	278.723	3.539	278.723	282.781	0.253	0.00%	1.44%
10-10-2-6	302.975	3.047	227.327	326.936	0.576	24.97%	30.47%
10-10-2-7	160.698	2.662	160.698	160.698	0.165	0.00%	0.00%
10-10-2-8	154.716	0.553	141.845	157.708	6.729	8.32%	10.06%
10-10-2-9	361.474	0.572	351.320	351.32	0.638	2.81%	0.00%
10-10-2-10	336.244	1.327	336.244	340.16	0.176	0.00%	1.15%
<b>Average</b>		<b>1.393</b>			<b>1.451</b>	<b>3.64%</b>	<b>4.72%</b>
20-20-4-1	874.862	3600	833.543	869.972	8.547	4.72%	4.19%
20-20-4-2	508.519	3600	493.011	514.088	1.285	3.05%	4.10%
20-20-4-3	679.000	3600	679.000	681.342	5.858	0.00%	0.34%
20-20-4-4	614.324	3600	580.729	618.129	4.173	5.47%	6.05%
20-20-4-5	578.069	3600	577.647	582.034	0.715	0.07%	0.75%
20-20-4-6	772.232	3600	657.137	774.538	4.097	14.90%	15.16%
20-20-4-7	593.113	3600	593.113	593.113	15.32	0.00%	0.00%
20-20-4-8	656.931	3600	649.399	671.055	6.798	1.15%	3.23%
20-20-4-9	663.387	3600	645.844	671.388	1.158	2.64%	3.80%
20-20-4-10	367.789	3600	393.445	398.014	1.035	-6.98%	1.15%
<b>Average</b>		<b>3600</b>			<b>4.899</b>	<b>2.50%</b>	<b>3.88%</b>
30-30-6-1	886.728	3600	863.675	901.12	6.315	2.60%	4.16%
30-30-6-2	--	3600	1001.41	1001.41	2.200	--	0.00%

<b>Instance</b>	$P_{\text{cplex}}$	$T_{\text{cplex}}(\text{s})$	$P_{\text{ls}}$	$D_{\text{ls}}$	$T_{\text{ls}}(\text{s})$	$\text{Gap}_{\text{ia/cplex}}$	$\text{Gap}_{\text{D/P}}$
30-30-6-3	--	3600	1280.25	1306.24	1.703	--	1.99%
30-30-6-4	1039.02	3600	1037.65	1098.36	17.74	0.13%	5.53%
30-30-6-5	--	3600	896.985	898.917	18.78	--	0.21%
30-30-6-6	1115.25	3600	1057.88	1130.36	16.41	5.14%	6.41%
30-30-6-7	889.337	3600	797.229	896.479	15.20	10.36%	11.07%
30-30-6-8	949.812	3600	933.327	989.136	9.743	1.74%	5.64%
30-30-6-9	--	3600	1156.60	1163.22	11.93	--	0.57%
30-30-6-10	770.3095	3600	695.076	790.088	13.50	9.77%	12.03%
<b>Average</b>		<b>3600</b>			<b>11.35</b>	<b>4.95%*</b>	<b>4.76%</b>
40-40-8-1	--		1212.13	1310.97	69.22	--	7.54%
40-40-8-2	--		1499.40	1529.37	16.46	--	1.96%
40-40-8-3	--		1669.68	1777.11	1.940	--	6.05%
40-40-8-4	--		1515.21	1580.43	13.15	--	4.13%
40-40-8-5	--		1678.63	1703.8	11.94	--	1.48%
40-40-8-6	--		1072.70	1092.96	20.34	--	1.85%
40-40-8-7	--		1589.70	1613.96	16.53	--	1.50%
40-40-8-8	--		1328.15	1422.1	16.35	--	6.61%
40-40-8-9	--		1253.78	1279.89	16.22	--	2.04%
40-40-8-10	--		1082.64	1246.27	4.715	--	13.13%
<b>Average</b>					<b>18.69</b>		<b>4.63%</b>
50-50-10-1	--		1527.55	1596.22	78.15	--	4.30%
50-50-10-2	--		1580.45	1729.47	7.627	--	8.62%
50-50-10-3	--		1958.56	2113.67	21.45	--	7.34%
50-50-10-4	--		1958.78	2055.94	15.74	--	4.73%
50-50-10-5	--		2338.44	2431.58	12.14	--	3.83%
50-50-10-6	--		1550.52	1557.59	18.63	--	0.45%
50-50-10-7	--		1777.85	1819.31	19.60	--	2.28%
50-50-10-8	--		1803.20	1958.09	13.50	--	7.91%
50-50-10-9	--		1518.19	1625.11	22.65	--	6.58%
50-50-10-10	--		1725.61	1848.76	4.885	--	6.66%
<b>Average</b>					<b>21.44</b>		<b>5.27%</b>

\*: the average value of the instances with a gap.

## 4.5 Chapter summary

This chapter studies a bid generation problem for a single carrier considering both requests required to serve in pre-exist commitments and requests to acquire in a combinatorial auction in which the carrier will participate. The problem is formulated as a mixed-integer linear programming model and a set partition model. A column generation algorithm is proposed to solve the problem whose subproblem is solved by a dynamic programming based labeling algorithm or a local search algorithm.

Computational results show that the column generation algorithm with local search can obtain a near-optimal solution for large instances of the problem quickly.

However, this algorithm needs to be improved further because the results of some test instances are not satisfactory. One way may be to construct better initial solution and use more effective local search operators. The other way is to combine column generation with branch and bound to devise a branch-and-price that can optimally solve the problem.

## **5 Model and Benders decomposition algorithm for a bid generation problem considering multiple periods and uncertainty**

### **5.1 Introduction**

As stated in Chapter 1, transportation service procurement (TSP) is often realized by combinatorial auction (CA). But the transportation service market is fiercely competed. To survive in this competition among the carriers and seek for more profits, the carriers need to have foresight when participating in a CA and making operation plans. That is to say, when a carrier plans its transportation operations, it must consider not only its present transportation requests but also the transportation requests it may acquire in future. In recent years, with the rolling horizon planning concept adopted in logistics, carriers usually plan their transportation operations of several periods (days) in advance. This implies that carriers must consider multiple periods when participating in a CA organized by shippers. Since transportation requests in future cannot be foreseen, carriers must consider request uncertainty in such auctions.

For each carrier, to adapt itself to the new trend in the industry, it needs to consider multiple periods (days) in its bid generation problem (BGP). When considering the BGP in a rolling horizon, a request open for bid in the transportation market may have a service window composed of several consecutive periods (days), and the request can be served in any period (day) within the window. In such a situation, the carrier needs to determine not only the requests to serve (bid) but also the period (day) to serve each of the requests in order to maximize its profit.

In a conventional single-period TSP auction, the requests open for bid are released before the auction, and a carrier may have requests acquired from shippers in former auctions or included in service contracts signed with shippers before. The carrier must consider the two types of requests, referred to as for-bid requests and reserved requests respectively hereafter, in solving its BGP. In addition, when the rolling horizon planning approach is adopted by a carrier, it must also consider transportation requests probably to appear in future in its BGP when it participates in an auction. The uncertainty of future requests in the trucking market makes the BGP

hard to solve, because some information about the future requests cannot be obtained in advance. Historical data can be used to develop routing strategies that improve service productivity (Seongmoon et al., 2005). To handle the uncertainty, carriers usually use the statistics of historical request data to predict future requests. With a long-time market experience, a carrier usually can estimate the probability of emergence of each future request. By considering the uncertainty of future requests in a probabilistic way, the bid generation problem studied in this chapter can better reflect the reality of truckload transportation market.

This chapter addresses a carrier's BGP in a TSP auction considering multiple periods and uncertainty, which is an extension of the BGP in Chapter 4. The decisions of the problem include the transportation requests to bid, the period to serve each request, and the routes to serve all requests including the carrier's reserved requests. This chapter contribute to this challenging problem in the following two aspects.

Firstly, by adopting the scenario approach of stochastic optimization, a mixed integer linear programming (MILP) model is formulated for the problem. The objective of the model is to maximize the total expected net profit of the carrier in a planning horizon of multiple periods. Inspired by Ergun et al. (Ö. Ergun et al., 2007a; Ö. Ergun et al., 2007b), the model adopts a formulation of lane covering problem (LCP), although our problem is a maximization problem. This model takes three types of requests into consideration: for-bid requests, i.e., requests open for bid, reserved requests that must be served by the carrier, and probabilistic requests whose emergence is uncertain. The routes to serve all requests are determined by solving a new variant of LCP with additional multi-period and probabilistic features. The reason for adopting the scenario approach to solve the problem approximately is its high complexity due to its stochastic nature. In this approach, each scenario corresponds to a possible realization of the random parameters (future requests) of the problem. For a given number of scenarios, the stochastic programming model of the problem can be transformed into a deterministic equivalence model, which can be solved optimally by an exact algorithm. According to the law of large numbers in probability theory, when the number of scenarios is taken sufficiently large, the solution of the deterministic equivalence model can well approximate the solution of the stochastic optimization problem.

Secondly, a Benders decomposition (BD) approach is proposed to solve the MILP model. In the approach, the original problem (model) is divided into many subproblems, one for each scenario. Based on the solutions of the subproblems, a

restricted master problem is solved with additional constraints (benders cuts) added in each iteration of the BD. To accelerate this iterative process, a technique of generating Pareto-optimal cuts (Magnanti & Wong, 1981) is applied in the BD. The performance of the proposed approach is evaluated by numerical experiments on multiple sets of randomly generated instances. A comparison with CPLEX solver on the instances demonstrates the BD approach is much more efficient than CPLEX solver in solving large instances. In addition, the value of considering probabilistic requests and multi-period in the BGP of CA is also evaluated.

The rest of the chapter is organized as follows. The description and mathematical formulation of the problem are provided in Section 5.2. In Section 5.3, the BD approach proposed to solve the problem is presented. Section 5.4 is devoted to the performance evaluation of the BD approach by comparing it with CPLEX solver and the evaluation of the value of considering probabilistic requests as well as multi-period in the BGP of CA on randomly generated instances. Section 5.5 concludes this chapter with perspectives for future research.

## **5.2 Problem description and deterministic equivalence model**

As introduced in Section 5.1, in this chapter, the multi-period BGP of a carrier takes three types of transportation requests into consideration: reserved requests, for-bid requests and probabilistic requests. The reserved requests are the ones that the carrier acquired in former contracts or past CA. Each request of this type must be served in a given period (day) as a commitment to its offering shipper. The for-bid requests are those open for bid in the imminent CA for TSP in which the carrier will participate. Each for-bid request can be served in any period within its time window composed of one or multiple consecutive periods. The carrier selects some for-bid requests to form its bid (a bundle of requests) in the CA. The probabilistic requests appear with a probability. Requests of this type may be given by long-term collaborating suppliers. Once such requests appear, the carrier need to add them into its transportation service plan. Probabilistic requests may also be used to model requests possibly acquired from spot transportation market in future auctions. Each request is associated with a revenue, which is the income that the carrier can generate by serving the request without taking into account any transportation cost incurred. For each for-bid request, its revenue corresponds to its asking price announced by the auctioneer in a multi-round CA described in the last section.

When a carrier makes a multi-period transportation planning, it usually adopts a

rolling horizon approach. Take five periods (working days) planning as an example. At the beginning of the first period, the carrier determines which requests to bid and makes route planning for the current period and the next four periods, i.e., periods 1 to 5, and the decisions for period 1 are implemented. After that, in period 2, the carrier will make bidding and routing decisions for periods 2 to 6 with information updated, and the decisions for period 2 will be implemented. This rolling horizon planning process will repeat. The multi-period BGP considered involves the decisions of a whole horizon.

There are two types of decisions that need to be made in the BGP. Firstly, the carrier must determine which request(s) to bid (choose), and in which periods each request will be served. Secondly, for each period, the carrier must determine the tours (routes) to serve all its requests. Since each request of truckload transportation can be represented by a lane with one origin and one destination, the studied bid generation problem can be formulated as a stochastic multi-period LCP with three types of lanes. Since probabilistic lanes may appear in future periods and which lanes to serve are decision variables, the BGP considered in this chapter is a new variant of LCP.

This BGP can be formulated on a complete directed graph  $G = (N, A)$  which represents a transportation network, where  $N$  is the set of nodes and  $A$  is the set of arcs in the graph. Each request or lane  $(i, j) \in A$  is characterized by an origin node  $i \in N$  and a destination node  $j \in N$ .

Before formulating the multi-period LCP, the following notations are firstly introduced:

---

**Sets:**

$N$ : the set of all nodes

$A$ : the set of all possible lanes

$T$ : the set of all periods

$L_t^r$ : the set of reserved lanes in period  $t$ ,  $t \in T$

$L^b$ : the set of for-bid lanes, each lane  $(i, j) \in L^b$  is associated with a time window

$$\left[ \underline{t}_{i,j}, \bar{t}_{i,j} \right] \subseteq T$$

$L_t^p$ : the set of probabilistic lanes in period  $t$ ,  $t \in T$

$$L_t^r, L^b, L_t^p \subseteq A$$

**Parameters:**

$C_{i,j}$ : the cost of traversing lane  $(i, j)$ ,  $(i, j) \in A$

$R_{i,j,t}^r$ : the revenue of serving reserved lane  $(i, j)$  in period  $t$ ,  $(i, j) \in L_t^r$ ,  $t \in T$

$R_{i,j,t}^b$ : the revenue (asking price) of serving for-bid lane  $(i, j)$ ,  $(i, j) \in L^b$

$R_{i,j,t}^p$ : the revenue of serving probabilistic lane  $(i, j)$  in period  $t$  if it appears,  
 $(i, j) \in L_t^p$ ,  $t \in T$

$$u_{i,j,t} = \begin{cases} 1, & \text{if there is a reserved lane } (i, j) \text{ in period } t, \\ 0, & \text{otherwise} \end{cases}$$

$(i, j) \in A$ ,  $t \in T$

$p_{i,j,t}$ : the probability of occurrence of probabilistic lane  $(i, j)$  in period  $t$

**Random variables:**

$$w_{i,j,t} = \begin{cases} 1, & \text{if probabilistic lane } (i, j) \text{ appears in period } t, \\ 0, & \text{otherwise} \end{cases}$$

$(i, j) \in L_t^p$ ,  $t \in T$

$w_{i,j,t}$  takes the value 1 with probability  $p_{i,j,t}$  and 0 with probability  $1 - p_{i,j,t}$

Here, it is assumed that each probabilistic lane  $(i, j)$  occurs at most once in each period  $t$ . With this assumption,  $w_{i,j,t}$  is a random variable with a Bernoulli distribution.

**Decision variables:**

$$v_{i,j,t} = \begin{cases} 1, & \text{if for-bid lane } (i, j) \text{ is chosen and served in period } t, \\ 0, & \text{otherwise} \end{cases};$$

$(i, j) \in A$ ,  $t \in T$

$x_{i,j,t}$ : the number of times that lane  $(i, j)$  is traversed by vehicles in period  $t$ ,  
 $(i, j) \in A$ ,  $t \in T$ .

---

To simplify the formulation, it is assumed that in each period, for any pair of origin and destination, there is at most one lane for each type, but different types of lanes can share the same origin and destination in each period. For example, if there is a reserved lane  $(i, j)$  in period  $t$ , there is no other reserved lane in this period with the same origin and destination, i.e.,  $u_{i,j,t} \leq 1$ , for any  $(i, j) \in L_t^r$ ,  $t \in T$ . However, a



for-bid lane  $(i, j)$  and/or probabilistic lane  $(i, j)$  can also exist in this period. The model and solution method proposed in this chapter can be easily extended to the case without such an assumption. This can be done by transforming the underlying transportation network in the following way: for each pair of origin node and destination node, if there are multiple lanes (say  $m > 1$  lanes) of the same type from the origin node to the destination node, one can create  $m$  copies of the two nodes (including original ones) with zero distance between any two copies of the origin node or the destination node such that only a single lane of this type exists from the  $i$ -th copy of the origin node to the  $i$ -th copy of the destination node ( $1 \leq i \leq m$ ).

This transformation will increase the size and the computational complexity of the BGP. However, our BGP can be considered a variant of the lane covering problem. A lane covering problem can be transformed into a min-cost flow problem, which can be solved by an algorithm of complexity  $O(n \log n(e + n \log n))$  (Orlin, 1993), where  $n$  is the number of nodes and  $e$  is the number of edges (arcs). So, the influence of this transformation on the size of the BGP is linear (the size of the transformed model is  $m$  times of that of the original model) and that on the complexity of the problem should be quadratic (the complexity of the transformed model is  $m^2$  times of that of the original model) in the worst case, where  $m$  is the maximum number of copies created for relevant nodes.

With the above notations and assumption, the problem studied can be formulated as the following model.

$P_0$ :

$$\text{Max}_{\{w_{i,j,t}\}} E \left\{ \sum_{t \in T} \sum_{(i,j) \in L^r} R_{i,j,t}^r + \sum_{t \in T} \sum_{(i,j) \in L^b} v_{i,j,t} R_{i,j,t}^b + \sum_{t \in T} \sum_{(i,j) \in L^p} w_{i,j,t} R_{i,j,t}^p - \sum_{t \in T} \sum_{(i,j) \in A} x_{i,j,t} C_{i,j} \right\}$$

s.t.

$$\sum_{j \in N} x_{i,j,t} = \sum_{j \in N} x_{j,i,t}; \quad i \in N, \quad t \in T \quad (5-1)$$

$$x_{i,j,t} \geq u_{i,j,t} + v_{i,j,t} + w_{i,j,t}; \quad (i, j) \in A, \quad t \in T \quad (5-2)$$

$$\sum_{t \in T} v_{i,j,t} \leq 1; \quad (i, j) \in L^b, \quad t \in [\underline{t}_{i,j}, \bar{t}_{i,j}] \quad (5-3)$$

$$v_{i,j,t} = 0; \quad (i, j) \in A \setminus L^b, \quad t \in T \quad (5-4)$$

$$v_{i,j,t} = 0; \quad (i, j) \in L^b, \quad t \in T \setminus [\underline{t}_{i,j}, \bar{t}_{i,j}] \quad (5-5)$$

The objective function is to maximize the total expected net profit in a planning horizon of multiple periods, which is the difference between the total revenue of all requests and the total cost for serving these requests including empty vehicle reposition costs. An empty vehicle reposition is a travel of an empty vehicle from one node to another node in the transportation network involved. Constraint (5-1) describes the vehicle flow equilibrium. That is, in each period, the number of vehicles arrive at each node equals to the number of vehicles leaving the node, which ensures the formation of a tour. Constraint (5-2) guarantees that all requests on lane  $(i, j)$ , if exist, are served. Constraint (5-3) indicates that if a for-bid lane is selected, it must be served in a period within its time (period) window. Constraint (5-4) ensures that the carrier will not serve any for-bid lane that does not exist. A for-bid lane will never be served in a period out of its time window, which is ensured by constraint (5-5).

Model  $P_0$  is a stochastic programming model, because there are random variables  $w_{i,j,t}$  in the model. This model cannot be solved easily by using an exact method because it contains both random variables and binary decision variables. For this reason, the popular scenario approach is adopted to solve the model approximately. In this approach, the stochastic programming model is transformed into a deterministic equivalence model for a give number of scenarios, where each scenario corresponds to a possible realization of all random variables in the former model. For an instance of model  $P_0$  with  $n$  probabilistic lanes, there are  $2^n$  possible scenarios in total. If  $n$  is large, it is difficult to consider all scenarios, so only part of the scenarios is considered. Let  $K$  be the set of all scenarios considered. Each individual scenario  $k \in K$  represents a particular realization (occurrence) of probabilistic lanes. In the deterministic equivalence model, the variables need to be reconsidered. For the random variable, the value of the variable  $w_{i,j,t}$  in each scenario  $k$  is given. Here a subscript  $k$  is added to  $w_{i,j,t}$  that represents its realization in scenario  $k$ , which makes it  $w_{i,j,t,k}$ . Then turn to the decision variables. On one hand, the decision variables  $v_{i,j,t}$  do not depend on any scenario because the BGP that determines which for-bid lanes to select is solved before the values of random variables  $w_{i,j,t}$  are observed. On the other hand, each decision variable  $x_{i,j,t}$  must be associated with all scenarios because the routing plan of the carrier in each period can only be made after the observation of the values of  $w_{i,j,t}$  in this period. Thus, decision variable  $v_{i,j,t}$  keeps intact and decision variable  $x_{i,j,t}$  becomes  $x_{i,j,t,k}$ . After considering scenarios, the deterministic equivalence model can now be formulated as

$P$ :

$$\text{Max} \sum_{t \in T} \sum_{(i,j) \in L_t^r} R_{i,j,t}^r + \sum_{t \in T} \sum_{(i,j) \in L_t^b} v_{i,j,t} R_{i,j,t}^b + \sum_{k \in K} \left( \sum_{t \in T} \sum_{(i,j) \in L_t^p} w_{i,j,t,k} R_{i,j,t}^p - \sum_{t \in T} \sum_{(i,j) \in A} x_{i,j,t,k} C_{i,j} \right) p_k$$

s.t.

$$\sum_{j \in N} x_{i,j,t,k} = \sum_{j \in N} x_{j,i,t,k}; \quad i \in N, t \in T, k \in K \quad (5-6)$$

$$x_{i,j,t,k} \geq u_{i,j,t} + v_{i,j,t} + w_{i,j,t,k}; \quad (i,j) \in A, t \in T, k \in K \quad (5-7)$$

and constraint (5-3) - (5-5)

In the objective function of model  $P$ , the parameter  $p_k$  represents the probability at which scenario  $k$  would happen. If all possible scenarios are taken into consideration, the value of  $p_k$  can be calculated from all  $p_{i,j,t}$ . Let  $L_{a,k}$  be the set of probabilistic lanes that will appear in scenario  $k$  and  $L_{b,k}$  be the set of probabilistic lanes that will not appear in scenario  $k$ . Then  $p_k$  can be calculated by the formula

$$\prod_{(i,j) \in L_{a,k}} \prod_{(i',j') \in L_{b,k}} p_{i,j,t} (1 - p_{i',j',t,k'}). \quad \text{Constraint (5-6) and (5-7) play the same role as}$$

constraint (5-1) and (5-2) respectively. The only difference is that the scenario subscript  $k$  is added to all scenario-dependent variables.

### 5.3 Benders decomposition approach for the deterministic equivalence model

As the stochastic programming problem considered is solved by using the scenario approach, its deterministic equivalence model has a special block structure. The scenarios can be taken as subproblems with exactly same structure. Due to this characteristic, a Benders decomposition approach is developed to solve this model. Benders decomposition is a technique that is often used to solve difficult mixed integer linear programming (MILP) problems and stochastic programming problems. It is an approach that exploits the structure of a MILP with complicated variables (Geoffrion, 1972). The basic idea of this approach is “divide and solve”. It partitions the variables of the original problem into two subsets, a set of integer variables and a set of continuous variables. It alternatively solves a subproblem (SP) and a restricted master problem (RMP) in each iteration. The SP is obtained by temporarily fixing the values of all integer variables to their values obtained by solving the RMP in the last iteration. Fixing the integer values makes the original problem tractable, because the SP is a linear programming problem. The RMP is a pure integer programming

problem except for one continuous variable. Compared with the master problem (the original MILP problem), RMP only contains part of the constraints of MILP and the constraints of the master problem will be added to RMP gradually in each iteration of Benders decomposition. In each iteration, one Benders cut (an inequality), either an optimality cut or a feasibility cut, is added to the RMP based on the solution of the SP. For a minimization original problem, the resolution of the SP and the RMP provides respectively an upper bound and a lower bound to the objective value of the original problem. The iterative process of Benders decomposition stops when a pre-specified stopping criterion is satisfied. One stopping criterion often used is the relative gap between the upper bound and the lower bound smaller than a given percentage, for example 1%.

To facilitate the formulation of the SP and RMP for the maximization MILP model  $P$ , firstly it needed to be transformed into a minimization model by rewriting its objective function as follows:

$$\text{Min} \sum_{k \in K} \left( \sum_{t \in T} \sum_{(i,j) \in A} x_{i,j,t,k} C_{i,j} - \sum_{t \in T} \sum_{(i,j) \in L_t^p} w_{i,j,t,k} R_{i,j,t}^p \right) p_k - \sum_{t \in T} \sum_{(i,j) \in L^b} v_{i,j,t} R_{i,j,t}^b - \sum_{t \in T} \sum_{(i,j) \in L_t^r} R_{i,j,t}^r$$

In the model, there are scenario-independent variables  $v_{i,j,t}$  and scenario-dependent variables  $x_{i,j,t,k}$ . The Benders' SP of the model is constructed by fixing the values of all  $v_{i,j,t}$  to  $\bar{v}_{i,j,t}$  for all  $t, i$ , and  $j$  in  $P$ . The SP then can be decomposed into  $|K|$  submodels  $SP_k$ ,  $k \in K$ , one for each scenario as

$SP_k$ :

$$\text{Min} \sum_{t \in T} \sum_{(i,j) \in A} x_{i,j,t,k} C_{i,j} - \sum_{t \in T} \sum_{(i,j) \in L_t^r} R_{i,j,t}^r - \sum_{t \in T} \sum_{(i,j) \in L^b} \bar{v}_{i,j,t} R_{i,j,t}^b - \sum_{t \in T} \sum_{(i,j) \in L_t^p} w_{i,j,t,k} R_{i,j,t}^p$$

s.t.

$$\sum_{j \in N} x_{i,j,t,k} = \sum_{j \in N} x_{j,i,t,k}; \quad i \in N, \quad t \in T \quad (5-8)$$

$$x_{i,j,t,k} \geq u_{i,j,t} + \bar{v}_{i,j,t} + w_{i,j,t,k}; \quad (i,j) \in A, \quad t \in T \quad (5-9)$$

In the first iteration of the Benders decomposition algorithm, the initial values of  $\bar{v}_{i,j,t}$  are set to  $\bar{v}_{i,j,t} = 0$  with which a feasible solution of the original model  $P$  exists.

In any other iteration, the values of  $\bar{v}_{i,j,t}$  are set to those in the solution of RMP

found in the last iteration. With the fixed values of  $\bar{v}_{i,j,t}$  and known values of  $w_{i,j,t,k}$  in each  $SP_k$ ,  $\sum_{t \in T} \sum_{(i,j) \in L^b} \bar{v}_{i,j,t} R_{i,j,t}^b$  and  $\sum_{t \in T} \sum_{(i,j) \in L^p} w_{i,j,t} R_{i,j,t}^p$  in its objective function are constants. Note that  $SP_k$  is a min-cost network flow problem whose optimal linear relaxation solution is always integral, so all its integer variables  $x_{i,j,t,k}$  can be relaxed to continuous (real) variables, i.e., each  $SP_k$  can be considered as a linear programming problem.

The dual problem of  $SP_k$  can be formulated as:

$DSP_k$ :

$$\begin{aligned} \text{Max} \quad & \sum_{(i,j) \in A} \sum_{t \in T} (\bar{v}_{i,j,t} + u_{i,j,t} + w_{i,j,t,k}) \lambda_{i,j,t,k} - \sum_{t \in T} \sum_{(i,j) \in L^r} R_{i,j,t}^r - \sum_{t \in T} \sum_{(i,j) \in L^b} \bar{v}_{i,j,t} R_{i,j,t}^b \\ & - \sum_{t \in T} \sum_{(i,j) \in L^p} w_{i,j,t,k} R_{i,j,t}^p \end{aligned}$$

s.t.

$$\sigma_{i,t,k} - \sigma_{j,t,k} + \lambda_{i,j,t,k} \leq C_{i,j}; \quad i, j \in A, \quad t \in T \quad (5-10)$$

$$\sigma_{i,t,k} \in \mathbb{R}; \quad i \in N, \quad t \in T \quad (5-11)$$

$$\lambda_{i,j,t,k} \geq 0; \quad i, j \in N, \quad t \in T \quad (5-12)$$

where  $\sigma_{i,t,k}$  and  $\lambda_{i,j,t,k}$  are the dual variables associated with constraint (5-8)

for  $i \in N$ ,  $t \in T$  and constraint (5-9) for  $(i, j) \in A$ ,  $t \in T$ , respectively.

The dual problem  $DSP_k$  can be either bounded or unbounded. If  $DSP_k$  is bounded, an extreme point which corresponds to its optimal solution can be obtained. Otherwise, an extreme ray of the linear programming model can be obtained.

Let DSP denote the dual problem of subproblem SP in our BD approach. Since SP is composed of  $|K|$  independent submodels  $SP_k$ ,  $k \in K$ , DSP is composed of  $|K|$  independent submodels  $DSP_k$ ,  $k \in K$ . SP is infeasible if any  $SP_k$  is infeasible, and DSP is unbounded if any  $DSP_k$  is unbounded. According to the duality theory of linear programming, SP has an optimal solution if DSP has an optimal solution. This happens when all  $DSP_k$  are bounded. In this case, an optimality constraint determined by the optimal solution (an extreme point) of DSP is added to the Benders' RMP. The

extreme point of the DSP is denoted by  $\{\mu_k, k \in K\}$  in which  $\mu_k$  is the extreme point of  $DSP_k$ . In the case that there is an unbounded  $DSP_k$ , SP is infeasible, then a feasibility constraint determined by an extreme ray of DSP is added to the RMP. This extreme ray can be obtained by combining an extreme ray of  $DSP_k$  and extreme rays or extreme points of the other  $DSP_{k'}$ ,  $k' \neq k$ . The extreme ray of DSP is denoted by  $\{\gamma_k, k \in K\}$  in which  $\gamma_k$  can be either an extreme point or an extreme ray of  $DSP_k$ .

The Benders decomposition algorithm is an iterative procedure. In each iteration, the SP and the RMP are solved alternately, and an optimality constraint (cut) or a feasibility constraint (cut) is added to the RMP according to whether the DSP is bounded or unbounded. Let  $\mu^p = \{\mu_k^p, k \in K\}$  denote the  $p$ -th extreme point of DSP, and  $\gamma^q = \{\gamma_k^q, k \in K\}$  denote  $q$ -th extreme ray of DSP, where  $p \in P$ ,  $q \in Q$ ,  $P$  and  $Q$  are the index set of all extreme points and the index set of all extreme rays of the DSP. Let  $\tilde{P} \subseteq P$  and  $\tilde{Q} \subseteq Q$  respectively denote the index set of the extreme points and the index set of the extreme rays of DSP found till the last iteration in this procedure.

By introducing real auxiliary variables  $z_k$ ,  $k \in K$ , the RMP of the BD approach can be formulated as

RMP:

$$\text{Min} \sum_{k \in K} z_k p_k - \sum_{t \in T} \sum_{(i,j) \in L^b} v_{i,j,t} R_{i,j,t}^b - \sum_{t \in T} \sum_{(i,j) \in L_t^r} R_{i,j,t}^r - \sum_{k \in K} \sum_{t \in T} \sum_{(i,j) \in L_t^p} w_{i,j,t,k} R_{i,j,t}^p$$

s.t.

$$z_k \geq \sum_{(i,j) \in A} \sum_{t \in T} (u_{i,j,t} + v_{i,j,t} + w_{i,j,t,k}) \mu_k^p; \quad k \in K, p \in \tilde{P} \quad (5-13)$$

$$\sum_{k \in K} \sum_{(i,j) \in A} \sum_{t \in T} (u_{i,j,t} + v_{i,j,t} + w_{i,j,t,k}) \gamma_k^q \leq 0; \quad q \in \tilde{Q} \quad (5-14)$$

and constraint (5-3) - (5-5)

For each iteration of BD, if the SP has an optimal solution, a constraint in form of (5-13) is added to the current RMP, if the subproblem is unbounded, a constraint in form of (5-14) is then added. As the number of iterations increases, the constraints accumulate with it.

For large-scale instances, the BD approach may iterate numerous times to obtain

an optimal solution. To accelerate the approach, pareto-optimal cuts can be generated and added to the RMP when some  $DSP_k$  have multiple optimal solutions by applying a technique proposed in the work of Magnanti and Wong (1981). A pareto-optimal cut is a cut that no other cut can dominate it. Each pareto-optimal cut is generated by solving a linear programming problem based on the optimal objective value of  $DSP_k$ . Let  $O_k$  denote the optimal objective value of  $DSP_k$  and  $\tilde{v}_{i,j,t}$  a point contained in the relative interior set of the polyhedron defined by constraints (5-3) - (5-5), the linear programming problem to generate the pareto-optimal cut for our problem can be formulated as

$POC_k$ :

$$\begin{aligned} \text{Max} \quad & \sum_{(i,j) \in A} \sum_{t \in T} (\tilde{v}_{i,j,t} + u_{i,j,t} + w_{i,j,t,k}) \lambda_{i,j,t,k} - \sum_{t \in T} \sum_{(i,j) \in L_t^r} R_{i,j,t}^r - \sum_{t \in T} \sum_{(i,j) \in L_t^b} \bar{v}_{i,j,t} R_{i,j,t}^b \\ & - \sum_{t \in T} \sum_{(i,j) \in L_t^p} w_{i,j,t,k} R_{i,j,t}^p \end{aligned}$$

s.t.

$$\begin{aligned} & \sum_{(i,j) \in A} \sum_{t \in T} (\bar{v}_{i,j,t} + u_{i,j,t} + w_{i,j,t,k}) \lambda_{i,j,t,k} - \sum_{t \in T} \sum_{(i,j) \in L_t^r} R_{i,j,t}^r - \\ & \sum_{t \in T} \sum_{(i,j) \in L_t^b} \bar{v}_{i,j,t} R_{i,j,t}^b - \sum_{t \in T} \sum_{(i,j) \in L_t^p} w_{i,j,t,k} R_{i,j,t}^p = O_k \end{aligned} \quad (5-15)$$

and constraint (5-10) - (5-12)

According to Magnanti and Wong (1981), the value of  $\tilde{v}_{i,j,t}$  is set to 0.5 for all  $t$ ,  $i$  and  $j$ . By solving  $POC_k$ , a new extreme point  $\{\mu_k, k \in K\}$  of DSP is obtained and a pareto-optimal cut in the same form as constraint (5-13) is then added to the RMP. The technique of adding pareto-optimal cuts can significantly accelerate the convergence of the BD approach. Numerical results in the literature have well proved the efficiency of this technique.

To sum up, the general procedure of the proposed BD approach for solving the deterministic equivalence model  $P$  can be described as follows, where  $\varepsilon$  is a pre-specified maximum relative error that is admissible between the upper bound (UB) and lower bound (LB) of the objective value of  $P$  found by the approach.

**Benders decomposition approach**


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{Initialization}
1   $\bar{v}_{i,j}^t :=$  the value of  $v_{i,j}^t$  in an initial feasible solution of  $P$ ,  $i \in N, j \in N, t \in T$ 
2   $LB := -\infty$ ,  $UB := +\infty$ 
{Main loop}
3  while  $(UB - LB) / LB > \varepsilon$  do
    {solve the subproblem (SP)}
4    for all  $k \in K$ , solve  $DSP_k$ 
5    if any  $DSP_k$  is unbounded then
6    get an extreme ray  $\mu_k^p$  for some  $p \in \tilde{P}$ 
7    else
8    solve  $POC_k$ 
9    get an extreme point  $\gamma_k^q$  for some  $q \in \tilde{Q}$  with  $\gamma_k^q =$ 
     $(\bar{x}_{i,j,t,k}, i \in N, j \in N, t \in T)$ 
10   generate a pareto-optimal cut (constraint) in the form of (5-13)
11   end if
12  end for
13  if all  $DSP_k, k \in K$  have an optimal solution
14  add  $|K|$  constraints in the form of (5-13) to  $RMP$ 
15  update  $UB := \min\{UB, \sum_{k \in K} O_k\}$ 
16  else one or more  $DSP_k$  are unbounded
17  add a constraint in the form of (5-14) to  $RMP$ 
18  end if
{solve the restricted master problem (RMP)}
19  solve  $RMP$  with newly added constraints
20  update  $LB := O_{RMP}$  which is the optimal objective value of the  $RMP$ 
21  update  $(\bar{v}_{i,j}^t)$  of  $DSP_k$  with the optimal solution of  $RMP$ 
{Output the results}
22  output the final solution  $(\bar{v}_{i,j}^t, \bar{x}_{i,j,t,k})$  and the corresponding objective value of  $P$ 

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**5.4 Computational experiments**

In this section, the efficiency of the proposed model and approach is evaluated as well as the value of considering probabilistic requests and multi-period in the BGP of CA by numerical experiments on randomly generated instances. The model is coded in C++ and solved by CPLEX. CPLEX solver is used as a benchmark for evaluating the efficiency of our BD method. The scenario-based BD algorithm is also coded in C++. All the tests are conducted on a PC with Intel® Core™ i7-8750H CPU and 16 GB RAM. The version of CPLEX is 12.10.0.0 for 64-bit Windows.



### 5.4.1 Experiment design

The values of the parameters used to generate the instances in the experiments are listed in Table 5-1. Among them, the number of reserved lanes, for-bid lanes and probabilistic lanes in the planning horizon are set to 10%, 10% and 5% of  $N^2T$  respectively, where  $N$  is the number of nodes in the transportation network and  $T$  is the number of periods. The coordinates of each node are integers randomly generated from 0 to 100. The origin node and destination node of each lane with request (i.e., reserved, for-bid or probabilistic lane) are randomly generated from the  $N$  nodes. The cost of each lane is given by the distance between its origin and destination. The revenue of serving each lane is set to its cost multiplied by a factor randomly generated from 1.0 to 2.0 with one decimal. For each instance, the emergence probability  $p_{i,j,t}$  of probabilistic lane  $(i, j) \in L_3^t$  in each period  $t \in T$  is randomly generated between 0.1 and 0.9. To determine whether a probabilistic lane  $(i, j)$  emerges in period  $t$  in each scenario  $k$ , a value  $r_{i,j,t,k}$  is generated randomly and uniformly from the interval  $[0, 1]$ , if  $r_{i,j,t,k} \leq p_{i,j,t}$ , then  $w_{i,j,t,k} = 1$ , otherwise  $w_{i,j,t,k} = 0$ .  $w_{i,j,t,k}$  generated in this way has a Bernoulli distribution with  $P\{w_{i,j,t,k} = 1\} = p_{i,j,t}$  and  $P\{w_{i,j,t,k} = 0\} = 1 - p_{i,j,t}$ , because  $r_{i,j,t,k}$  is uniformly distributed random variable defined on  $[0,1]$ , so  $P\{w_{i,j,t,k} = 1\} = P\{r_{i,j,t,k} \leq p_{i,j,t}\} = p_{i,j,t}$  and  $P\{w_{i,j,t,k} = 0\} = P\{r_{i,j,t,k} > p_{i,j,t}\} = 1 - p_{i,j,t}$ . In this way, for each instance, the total number of the three types of lanes generated account for about 25% of all lanes in the transportation network, and only some of for-bid lanes are chosen by the carrier.

As mentioned before, in the scenario approach for stochastic optimization, each possible realization of all random variables/parameters of a stochastic programming problem is considered a scenario. Although the total number of scenarios may be very large, according to the theory of Monte-Carlo sampling, not all scenarios are needed to enumerate to obtain a solution close to the true optimal solution at a high probability. That is, if the number of scenarios is taken sufficiently large, it can be ensured that the solution found by our scenario approach is within an interval including the true optimal solution at a given probability (in terms of net profit). The interval and probability are referred to as confidence interval and confidence level, respectively. The required scenario size can be determined by numerical experiments.

According to Geweke and Singleton (1980), and You et al. (2009) on Monte-Carlo sampling, here first generates several instances randomly with the number of nodes  $N = 10, 20, 30, 40, 50$  and set the number of scenarios to  $K_0 = 30$ , and then for each instance the standard deviation  $S(K_0)$  of the net profit of model  $P$

obtained under each scenario is calculated. For a given confidence interval with length  $H$  and a given confidence level  $\alpha$  with  $0 < \alpha < 1$ , the required scenario size  $K$  can be calculated by the formula:

$$K = \max\left(\left[\frac{z_{\alpha/2}S(K_0)}{H}\right]^2, K_0\right)$$

where  $z_{\alpha/2}$  is the  $z$ -value of the standard normal distribution defined as  $P(x \leq z_{\alpha/2}) = 1 - \alpha/2$ ,  $x \sim N(0,1)$ . Here chooses confidence level  $\alpha = 95\%$  and confidence interval with relative error  $\pm 1\%$  with respect to the true optimal solution in terms of profit. The statistical results show that 100 scenarios are adequate for all instances with 50 nodes or less.

Table 5-1 Parameters for the generation of instances

<i>Item</i>	<i>Value</i>
Number of reserved lanes	$N^2T * 0.1$
Number of for-bid lanes	$N^2T * 0.1$
Number of probabilistic lanes	$N^2T * 0.05$
Coordinates $(x_i, y_i)$ of each node $i \in N$	$U[0, 100] \times [0, 100]$
Cost of a lane $(i, j)$	$\sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$
Revenue of serving a lane	$(1.0 \sim 2.0) * \text{Cost}$
Emergence probability of a probabilistic lane	$0.1 \sim 0.9$

### 5.4.2 Evaluation of the proposed model and solution approach

Firstly, three groups of experiments are conducted to evaluate the performance of our proposed model and BD approach. The first group with different numbers of nodes is used to evaluate the efficiency of the proposed BD approach with respect to CPLEX solver. The second group with different sizes of scenarios is used to evaluate the impact of scenario size on the computational efficiency of the BD approach and CPLEX solver. The third group with different number of probabilistic lanes is used to evaluate the impact of the request uncertainty on the computational efficiency of the BD approach and CPLEX solver. In all tests, the maximum relative error  $\varepsilon$  for stopping BD is set as 0.1%. Accordingly, the relative tolerance of gap of CPLEX solver is also as 0.1%.

For the first group of experiments, 5 sets of instances are tested with the number of nodes  $N = 10, 20, 30, 40$  and  $50$ , respectively. For each set, 10 instances are

randomly generated. As discussed above, the scenario number is set to 100 for all instances to maintain the consistency among all instance sets. The number of periods is set as  $T = 5$  corresponding to five working days each week. Each instance is represented by its number of nodes, number of scenarios, and a serial number in its instance set. For example, instance 20-100-3 represents the third instance in the instance set with 20 nodes and 100 scenarios. The performance of CPLEX solver and the BD approach for solving the model is given in Table 5-2, where  $OPT_C$  and  $OPT_B$  denote the optimal objective value of the model found by CPLEX and the BD approach respectively, and  $T_C$  and  $T_B$  denote their corresponding CPU times to obtain a solution with the relative optimality gap 0.1%. Note that  $OPT_C$  and  $OPT_B$  may be slightly different for some instances because CPLEX and the BD approach may stop at different gaps although they are both less than or equal to 0.1%.

Table 5-2 Results for CPLEX and BD approach with different problem scales

Instance	CPLEX		BD		$T_C / T_B$	AVG $T_C / T_B$
	$OPT_C$	$T_C$ (s)	$OPT_B$	$T_B$ (s)		
10-100-1	1749.99	0.731	1749.99	1.165	0.63	
10-100-2	1145.78	0.724	1145.78	1.102	0.66	
10-100-3	1755.34	0.741	1755.34	1.068	0.69	
10-100-4	1528.89	0.762	1528.89	1.088	0.70	
10-100-5	973.932	0.730	973.932	1.077	0.68	
10-100-6	1064.23	0.710	1064.23	1.147	0.62	0.69
10-100-7	963.605	0.753	963.605	0.978	0.77	
10-100-8	1200.01	0.727	1200.01	1.022	0.71	
10-100-9	1138.44	0.699	1138.44	0.999	0.70	
10-100-10	2167.84	0.697	2167.84	0.982	0.71	
20-100-1	8322.54	11.317	8322.54	7.997	1.42	
20-100-2	8452.54	11.853	8452.54	7.181	1.65	
20-100-3	10017.3	10.499	10017.3	8.571	1.22	
20-100-4	9238.67	12.358	9238.67	6.239	1.98	
20-100-5	6706.70	9.310	6706.70	7.875	1.18	
20-100-6	7254.12	11.677	7254.12	20.645	0.57	1.54
20-100-7	8101.11	14.077	8101.11	8.490	1.66	
20-100-8	6974.10	19.587	6974.32	9.922	1.97	
20-100-9	7731.40	9.494	7731.40	6.458	1.47	
20-100-10	8031.64	13.927	8031.64	6.171	2.26	
30-100-1	18546.7	157.215	18531.8	31.756	4.95	
30-100-2	21669.3	93.592	21676.2	30.799	3.04	
30-100-3	21551.7	164.819	21548.4	31.182	5.29	4.79
30-100-4	19648.9	161.813	19648.9	30.827	5.25	
30-100-5	19396.0	226.043	19382.3	33.835	6.68	

Instance	CPLEX		BD		$T_C/T_B$	AVG $T_C/T_B$
	$OPT_C$	$T_C$ (s)	$OPT_B$	$T_B$ (s)		
30-100-6	18508.8	196.205	18506.4	32.613	6.02	
30-100-7	20361.3	131.856	20361.3	41.619	3.17	
30-100-8	20796.5	139.974	20799.7	31.495	4.44	
30-100-9	20451.3	173.782	20448.5	30.213	5.75	
30-100-10	20766.5	117.977	20799.2	36.121	3.27	
40-100-1	37074.9	895.901	37064.5	76.154	11.76	
40-100-2	41636.2	682.359	41627.1	67.073	10.17	
40-100-3	42051.1	1212.01	42044.1	76.074	15.93	
40-100-4	37791.5	1018.58	37777.0	100.635	10.12	
40-100-5	35992.8	592.980	36004.2	76.879	7.71	
40-100-6	33198.5	791.103	33185.5	71.315	11.09	11.20
40-100-7	37323.7	972.670	37316.3	77.509	12.55	
40-100-8	39032.1	1249.30	39015.7	120.028	10.41	
40-100-9	36544.0	1067.63	36543.5	73.274	14.57	
40-100-10	35338.3	747.630	35363.6	97.133	7.70	
50-100-1	56176.3	2894.46	56159.2	260.497	11.11	
50-100-2	66720.7	3871.80	66679.2	360.398	10.74	
50-100-3	62338.4	3840.76	62314.5	765.759	5.02	
50-100-4	60315.6	2438.29	60328.7	177.981	13.70	
50-100-5	58057.6	3597.14	58032.5	126.407	28.46	
50-100-6	52973.7	2624.68	52964.0	203.314	12.91	14.15
50-100-7	59561.2	2352.05	59561.9	115.337	20.39	
50-100-8	59023.3	3713.28	59032.3	256.462	14.48	
50-100-9	58731.9	2261.17	58764.7	165.876	13.63	
50-100-10	60469.0	2139.34	60499.3	192.718	11.10	

From Table 5-2, it can be observed that both CPLEX solver and the BD approach can obtain a solution with the allowable relative optimality gap in a reasonable time. However, the difference between  $T_C$  and  $T_B$  becomes very significant when the number of nodes exceeds 20. For small instances with  $N = 10$ , CPLEX solver can solve them in less time, but when the number of nodes increases, the superiority of the BD approach over CPLEX solver in computational efficiency becomes more and more evident. For the set of instances with 50 nodes and 100 scenarios, the BD approach can solve most instances within 300 seconds, whereas CPLEX solver requires more than 14 times of the BD's computation time for these instances on average.

For the second group of experiments, only instances with  $N = 30$  and 40 are considered, which evidently show the computation time difference between CPLEX

solver and the BD approach in solving the BGP. The number of scenarios is set as  $K = 100, 125$  and  $150$ . The number of periods is kept at  $T = 5$ .

The results of this group given in Table 5-3 show that as the number of scenarios increases,  $T_C / T_B$  increases. Take instances with 30 nodes as an example, when the number of scenarios increases from 100 to 150, the average of  $T_C / T_B$  increases from 4.79 to 7.33, which implies that the computational efficiency of the BD approach becomes more notable with respect to CPLEX solver when the scenario size increases. This is because the BD approach can take advantage of the decomposition of SP into submodels  $SP_k$ ,  $k \in K$  when the number of scenarios is large.

Note that there is an attempt to conduct more experiments on instances with larger number of nodes and larger number of scenarios, but CPLEX solver went out of memory for those instances. The results mentioned above are sufficient to demonstrate that the BD approach is more efficient than CPLEX solver in terms of computation time.

Table 5-3 Results for CPLEX and BD approach with different number of scenarios

Instance	CPLEX		BD		$T_C / T_B$	AVG $T_C / T_B$
	$OPT_C$	$T_C$ (s)	$OPT_B$	$T_B$ (s)		
30-100-1	18546.7	157.215	18531.8	31.756	4.95	
30-100-2	21669.3	93.592	21676.2	30.799	3.04	
30-100-3	21551.7	164.819	21548.4	31.182	5.29	
30-100-4	19648.9	161.813	19648.9	30.827	5.25	
30-100-5	19396.0	226.043	19382.3	33.835	6.68	
30-100-6	18508.8	196.205	18506.4	32.613	6.02	4.79
30-100-7	20361.3	131.856	20361.3	41.619	3.17	
30-100-8	20796.5	139.974	20799.7	31.495	4.44	
30-100-9	20451.3	173.782	20448.5	30.213	5.75	
30-100-10	20766.5	117.977	20779.2	36.121	3.27	
30-125-1	18543.3	266.222	18546.2	51.378	5.18	
30-125-2	21651.6	184.311	21650.4	38.790	4.75	
30-125-3	21578.8	229.609	21572.8	38.627	5.94	
30-125-4	19667.3	268.123	19655.1	41.751	6.42	
30-125-5	19399.2	278.740	19399.1	43.768	6.37	
30-125-6	18518.0	372.295	18514.0	43.374	8.58	5.77
30-125-7	20348.6	245.183	20349.4	59.211	4.14	
30-125-8	20804.6	229.479	20799.7	38.054	6.03	
30-125-9	20442.4	209.630	20435.2	39.466	5.31	
30-125-10	20791.3	212.715	20791.0	43.259	4.92	
30-150-1	18550.7	410.425	18545.5	52.910	7.76	7.33

Instance	CPLEX		BD		$T_C / T_B$	AVG $T_C / T_B$
	$OPT_C$	$T_C$ (s)	$OPT_B$	$T_B$ (s)		
30-150-2	21640.2	279.926	21622.6	49.509	5.65	
30-150-3	21583.1	417.433	21578.8	51.247	8.15	
30-150-4	19651.7	333.241	19663.1	53.575	6.22	
30-150-5	19379.3	638.319	19380.9	55.896	11.42	
30-150-6	18515.1	505.737	18514.5	54.766	9.23	
30-150-7	20339.7	443.483	20340.8	81.959	5.41	
30-150-8	20803.7	401.041	20801.8	60.762	6.60	
30-150-9	20419.5	315.244	20417.0	50.550	6.24	
30-150-10	20784.2	326.429	20784.2	49.220	6.63	
40-100-1	37074.9	895.901	37064.5	76.154	11.76	
40-100-2	41636.2	682.359	41627.1	67.073	10.17	
40-100-3	42051.1	1212.01	42044.1	76.074	15.93	
40-100-4	37791.5	1018.58	37777.0	100.635	10.12	
40-100-5	35992.8	592.980	36004.2	76.879	7.71	11.20
40-100-6	33198.5	791.103	33185.5	71.315	11.09	
40-100-7	37323.7	972.670	37316.3	77.509	12.55	
40-100-8	39032.1	1249.30	39015.7	120.028	10.41	
40-100-9	36544.0	1067.63	36543.5	73.274	14.57	
40-100-10	35338.3	747.630	35363.6	97.133	7.70	
40-125-1	37073.7	1210.84	37047.4	94.450	12.82	
40-125-2	41623.4	1117.10	41631.0	81.147	13.77	
40-125-3	42038.4	1803.15	42014.3	198.125	9.10	
40-125-4	37793.9	1630.55	37762.5	139.134	11.72	
40-125-5	36024.2	1147.71	35994.6	84.384	13.60	11.25
40-125-6	33199.3	1222.69	33173.8	82.374	14.84	
40-125-7	37300.8	933.134	37324.6	121.866	7.66	
40-125-8	38990.9	2005.20	38994.7	368.005	5.45	
40-125-9	36575.2	1562.64	36553.6	99.861	15.65	
40-125-10	35341.0	1031.78	35347.4	130.590	7.90	
40-150-1	37042.8	1591.11	37036.1	128.612	12.37	
40-150-2	41627.1	1659.65	41631.3	102.147	16.25	
40-150-3	42038.8	2294.24	42020.9	214.105	10.72	
40-150-4	37802.4	2158.02	37778.1	196.492	10.98	
40-150-5	35981.8	1536.61	35982.9	103.718	14.82	14.09
40-150-6	33183.7	3138.96	33166.2	139.891	22.44	
40-150-7	37296.6	1346.26	37321.9	152.748	8.81	
40-150-8	39002.9	2595.49	38994.0	383.306	6.77	
40-150-9	36578.8	2970.42	36561.6	117.011	25.39	
40-150-10	35358.1	1876.66	35346.3	151.754	12.37	

For the third group of experiments, instances with  $N = 30$  and 40 are still

considered, but with different number of probabilistic lanes, which is 5%, 10% and 15% of  $N^2T$  respectively. The number of reserved lanes and for-bid lanes remains as set in Table 5-1. The results of this group are given in Table 5-4, where each instance is represented by its node number, number of probabilistic lanes in percentage of  $N^2T$ , and a serial number. For example, instance 30-5%-2 is the second instance with 30 nodes and the number of probabilistic lanes set as 5% of  $N^2T$ .

From Table 5-4, it can be seen that as the number of probabilistic lanes increase, the advantage of the BD approach over CPLEX solver in computation time seems slightly reduced, but the computation time of BD is still much less than CPLEX.

Table 5-4 Results with different number of probabilistic lanes

Instance	CPLEX		BD		$T_C/T_B$	AVG $T_C/T_B$
	$OPT_C$	$T_C$ (s)	$OPT_B$	$T_B$ (s)		
30-5%-1	18546.7	157.215	18531.8	31.756	4.95	
30-5%-2	21669.3	93.592	21676.2	30.799	3.04	
30-5%-3	21551.7	164.819	21548.4	31.182	5.29	
30-5%-4	19648.9	161.813	19648.9	30.827	5.25	
30-5%-5	19396.0	226.043	19382.3	33.835	6.68	
30-5%-6	18508.8	196.205	18506.4	32.613	6.02	4.79
30-5%-7	20361.3	131.856	20361.3	41.619	3.17	
30-5%-8	20796.5	139.974	20799.7	31.495	4.44	
30-5%-9	20451.3	173.782	20448.5	30.213	5.75	
30-5%-10	20766.5	117.977	20779.2	36.121	3.27	
30-10%-1	20414.9	186.714	20403.9	33.487	5.58	
30-10%-2	24510.4	120.934	24526.5	29.099	4.16	
30-10%-3	23870.6	89.188	23870.7	49.142	1.81	
30-10%-4	21533.5	155.328	21516.5	31.188	4.98	
30-10%-5	21268.9	143.944	21268.9	29.833	4.82	
30-10%-6	20274.1	125.098	20274.0	39.326	3.18	4.31
30-10%-7	22571.9	212.810	22567.3	52.888	4.02	
30-10%-8	23164.7	191.116	23155.6	30.662	6.23	
30-10%-9	22463.3	103.639	22457.1	23.434	4.42	
30-10%-10	23349.1	147.982	23359.8	38.551	3.84	
30-15%-1	22323.5	139.682	22323.5	32.163	4.34	
30-15%-2	26934.8	68.649	26934.8	26.666	2.57	
30-15%-3	26262.6	85.574	26247.9	49.543	1.73	
30-15%-4	24164.3	115.938	24164.9	29.022	3.99	
30-15%-5	23121.9	210.288	23112.2	31.805	6.61	4.11
30-15%-6	22316.2	129.313	22323.5	35.892	3.60	
30-15%-7	25087.7	177.070	25086.6	51.764	3.42	
30-15%-8	24992.8	124.499	24997.5	21.784	5.72	

Instance	CPLEX		BD		$T_C/T_B$	AVG $T_C/T_B$
	$OPT_C$	$T_C$ (s)	$OPT_B$	$T_B$ (s)		
30-15%-9	24806.8	119.501	24801.0	23.041	5.19	
30-15%-10	25803.0	143.322	25805.3	36.911	3.88	
40-5%-1	37074.9	895.901	37064.5	76.154	11.76	
40-5%-2	41636.2	682.359	41627.1	67.073	10.17	
40-5%-3	42051.1	1212.01	42044.1	76.074	15.93	
40-5%-4	37791.5	1018.58	37777.0	100.635	10.12	
40-5%-5	35992.8	592.980	36004.2	76.879	7.71	11.20
40-5%-6	33198.5	791.103	33185.5	71.315	11.09	
40-5%-7	37323.7	972.670	37316.3	77.509	12.55	
40-5%-8	39032.1	1249.30	39015.7	120.028	10.41	
40-5%-9	36544.0	1067.63	36543.5	73.274	14.57	
40-5%-10	35338.3	747.630	35363.6	97.133	7.70	
40-10%-1	41065.2	598.409	41072.2	69.041	8.67	
40-10%-2	45638.9	964.150	45639.9	65.376	14.75	
40-10%-3	46573.3	839.832	46534.3	64.864	12.95	
40-10%-4	41868.6	876.652	41847.8	70.147	12.50	
40-10%-5	40085.1	545.284	40107.6	104.569	5.21	9.69
40-10%-6	37208.9	539.183	37197.5	77.100	6.99	
40-10%-7	40993.7	663.420	40984.0	56.702	11.70	
40-10%-8	43033.7	758.435	43041.6	70.310	10.79	
40-10%-9	41201.7	720.490	41203.0	85.144	8.46	
40-10%-10	39510.6	477.038	39518.3	97.758	4.88	
40-15%-1	45021.7	780.784	44998.5	62.680	12.46	
40-15%-2	50224.8	627.817	50189.9	60.560	10.37	
40-15%-3	50763.7	936.781	50726.4	72.570	12.91	
40-15%-4	46230.4	594.639	46219.6	59.472	10.00	
40-15%-5	43917.2	632.864	43949.8	78.993	8.01	10.52
40-15%-6	40603.8	924.588	40570.0	59.484	15.54	
40-15%-7	45023.0	409.014	45019.2	86.173	4.75	
40-15%-8	47619.4	994.470	47586.9	64.828	15.34	
40-15%-9	45711.1	663.272	45715.4	59.723	11.11	
40-15%-10	44312.0	539.861	44307.4	113.843	4.74	

To make comparison results more convincing, some more realistic instances with datasets taken from the website of Heidelberg University are also tested. To fit the characteristics of our problem, two datasets for travelling salesman problem (TSP) on the site are chosen, one is “berlin52” with 52 locations in Berlin, another is “bays29” with 29 locations in Bavaria. The results given in Table 5-5 shows that for these instances, the BD approach still outperforms CPLEX in solving the BGP, and the time ratio  $T_C / T_B$  has a similar trend as that for randomly generated instances when the



number of nodes increases.

Table 5-5 Results for Datasets “bays29” and “berlin52” with 5% Probabilistic Lanes

Instance	CPLEX		BD		$T_C/T_B$	AVG $T_C/T_B$
	$OPT_C$	$T_C$ (s)	$OPT_B$	$T_B$ (s)		
bays29-1	71195.2	102.993	71195.2	27.442	3.75	
bays29-2	74116.7	60.897	74115.1	21.371	2.85	
bays29-3	73687.0	72.007	73673.6	26.108	2.76	
bays29-4	70179.9	84.512	70137.6	28.425	2.97	
bays29-5	71357.7	175.242	71306.6	33.146	5.29	
bays29-6	71972.8	105.006	71985.5	26.814	3.92	3.54
bays29-7	69335.7	99.999	69335.7	24.041	4.16	
bays29-8	75128.4	65.584	75128.4	27.069	2.42	
bays29-9	75658.6	105.111	75658.6	31.704	3.32	
bays29-10	73831.7	118.839	73791.9	29.845	3.98	
berlin52-1	706536	4785.19	706101	281.017	17.03	
berlin52-2	713858	3952.09	713818	265.104	14.91	
berlin52-3	719234	3272.39	719259	134.582	24.32	
berlin52-4	739907	3462.91	739693	140.687	24.61	
berlin52-5	722906	3455.18	723071	151.124	22.86	
berlin52-6	717613	4637.84	717550	148.408	31.25	22.77
berlin52-7	713145	3109.39	712940	122.846	25.31	
berlin52-8	710285	3063.88	710476	149.851	20.45	
berlin52-9	716058	3131.58	716229	151.035	20.73	
berlin52-10	718642	3669.49	718361	139.734	26.26	

#### 5.4.3 Value of considering probabilistic requests in bid generation

Secondly, the value of considering probabilistic requests in the BGP is evaluated by comparing its expected net profits obtained with and without considering the probabilistic requests, respectively.

The BGP that considers probabilistic requests has been addressed above as well as its expected net profit. The corresponding BGP without considering probabilistic requests is the one that ignores all probabilistic requests when it generates a bid, and the carrier will reconstruct its vehicle routes when the probabilistic requests appear later. The expected net profit of the carrier obtained by the second BGP can be obtained by calculating the expected net profit of the first BGP at the solution (bid) of the second BGP as the value of a stochastic solution in stochastic programming is evaluated. It is assumed that in both cases, the carrier wins the bid generated by its BGP.

Here sets  $N = 30$ ,  $T = 5$ , and  $K = 100$  for all instances randomly generated for this evaluation. The numbers of three types of lanes are set the same as those in the corresponding instances in the third group of experiments. The expected net profit of

the carrier in both cases is estimated by its average net profit obtained in 100 scenarios. The results of comparison of the two BGPs are presented in Table 5-6, where  $NP_{with}$  and  $NP_{without}$  denote the average net profits of the carrier obtained by its BGP with and without considering probabilistic requests respectively, and Gap is calculated as  $(NP_{with} - NP_{without})/NP_{without}$ .

From Table 5-6, it can be found that considering probabilistic requests in the BGP can increase the expected net profit of the carrier compared with that without considering probabilistic requests. The results in this table also show that the higher the request uncertainty the carrier faces when it makes its bidding decision, the more expected profit increase it can obtain by considering probabilistic requests in its BGP. Since the profit margins of most carriers are quite small in the current competitive transportation market, even 2~4% increase of net profit is valuable for a carrier to improve its competitive advantage over other carriers, the results demonstrate the necessity of considering request uncertainty in the bid generation of a carrier when it participates in a CA for transportation service procurement.

Table 5-6 Results for Evaluation of the Value of Considering Probabilistic Requests

Instance	$NP_{with}$	$NP_{without}$	Gap	AVG Gap
30-5%-1	18546.7	18271.6	1.51%	
30-5%-2	21669.3	20834	4.01%	
30-5%-3	21511.7	21114.6	1.88%	
30-5%-4	19648.9	19097	2.89%	
30-5%-5	19396.0	18882.3	2.72%	
30-5%-6	18508.8	18064.9	2.46%	2.63%
30-5%-7	20361.3	19770.8	2.99%	
30-5%-8	20796.5	20229.4	2.80%	
30-5%-9	20451.3	19956.4	2.48%	
30-5%-10	20766.5	20252.5	2.54%	
30-10%-1	20414.9	19758.8	3.32%	
30-10%-2	24510.4	23642.2	3.67%	
30-10%-3	23870.6	23304.2	2.43%	
30-10%-4	21533.5	20793.3	3.56%	
30-10%-5	21268.9	20484.5	3.83%	
30-10%-6	20274.1	19548.6	3.71%	3.37%
30-10%-7	22571.9	21850.5	3.30%	
30-10%-8	23164.7	22554.2	2.71%	
30-10%-9	22463.3	21686	3.58%	
30-10%-10	23349.1	22549.3	3.55%	
30-15%-1	22323.5	21499.9	3.83%	
30-15%-2	26934.8	25779.1	4.48%	4.01%

<b>Instance</b>	<b><math>NP_{with}</math></b>	<b><math>NP_{without}</math></b>	<b>Gap</b>	<b>AVG Gap</b>
30-15%-3	26262.6	25514.7	2.93%	
30-15%-4	24164.3	23141	4.42%	
30-15%-5	23121.9	21971.1	5.24%	
30-15%-6	22316.2	21486.3	3.86%	
30-15%-7	25087.7	24138.5	3.93%	
30-15%-8	24992.8	23991.1	4.18%	
30-15%-9	24806.8	23808.5	4.19%	
30-15%-10	25803	25043.2	3.03%	

#### 5.4.4 Value of considering multi-period in bid generation

Thirdly, the value of considering multi-period in the bid generation of a carrier is evaluated. In order to do so, multi-period BGP with single-period BGP for a carrier participating in a multi-round CA of truckload transportation service procurement are compared with three carriers. The auction mechanism used in the CA is combinatorial clock auction which was often used in auctions for collaborative logistics and for allocating radio spectrum licenses. The outcomes of the CA are compared in two scenarios: all carriers adopt single-period BGP for their bidding decisions in the first scenario and one carrier adopts multi-period BGP and the others adopt single-period BGP for their bidding decisions in the second one. The planning horizon of the carrier in its multi-period BGP is set to 5 periods, i.e.,  $T = 5$ , and the CA for 20 periods is simulated. Other parameters of the instances tested in this evaluation are set as:  $N = 20$ ,  $K = 100$ , and the number of reserved lanes, for-bid lanes, and probabilistic lanes set as 10%, 10% and 5% of all possible lanes respectively on average for each carrier in each period. For the CA conducted in each period, the earliest possible service period of each for-bid lane is set as the current period and the latest possible service period is randomly generated within the 5 periods starting from the current period. The CA in each period is stopped when all for-bid lanes are sold out or the number of rounds reaches 50. To eliminate the influence of the initial conditions especially reserved requests on the outcome of the CA in each period and the corresponding net profit of each carrier, only the results of the auctions of 15 periods are recorded, that is, the first 5 periods are taken as warm-up periods.

In addition, in this simulation, if a carrier adopts single-period BGP, its selected for-bid lanes (lanes to bid) must be served in the current period. Otherwise, if a carrier adopts multi-period BGP, its selected for-bid lanes can be served in any period within their time windows.

Five instances are randomly generated in this evaluation. Table 5-7 compares the

net profits gained and the percentages of for-bid lanes (with respect to all for-bid lanes) won by the considered carrier when it adopts single-period BGP and multi-period BGP respectively, while all other carriers adopt single-period BGP, where  $NP_s$  and  $NP_m$  denote the net profit of the carrier obtained by adopting single-period BGP and multi-period BGP respectively, and  $P_s$  and  $P_m$  denote the percentage of for-bid lanes won by the carrier by adopting single-period BGP and multi-period BGP respectively.

From Table 5-7, it can be observed that if the carrier adopts multi-period BGP in the CA, its net profit can significantly increase compared with the case when it adopts single-period BGP. The increase of the average net profit per period of the carrier is between 14% to 25%. This increase indicates by considering multiple periods, the carrier can win more for-bid lanes which are complementary with its reserved lanes not only in the current period but also in the other periods in its planning horizon so that these for-bid lanes can be served with lower costs compared with its competitors (the other carriers).

Table 5-7 Results for Evaluation of the Value of Considering Multi-period in BGP

Instance - Period	$NP_s$	$NP_m$	$(NP_m - NP_s) / NP_s$	$P_s$	$P_m$	$P_m - P_s$
1-1	779.435	970.72	24.54%	0.00%	50.62%	50.62%
1-2	1053.71	1077.07	2.22%	48.57%	65.79%	17.22%
1-3	912.606	746.842	-18.16%	44.59%	49.35%	4.76%
1-4	806.38	795.102	-1.40%	46.05%	61.64%	15.59%
1-5	844.972	1022.09	20.96%	39.02%	62.50%	23.48%
1-6	820.558	963.485	17.42%	48.10%	67.11%	19.00%
1-7	689.862	913.29	32.39%	0.00%	59.49%	59.49%
1-8	629.471	873.105	38.70%	0.00%	60.76%	60.76%
1-9	1091.97	986.98	-9.61%	59.74%	65.85%	6.11%
1-10	795.764	894.788	12.44%	48.61%	59.21%	10.60%
1-11	649.201	1010.14	55.60%	0.00%	61.64%	61.64%
1-12	841.298	989.426	17.61%	33.80%	56.76%	22.95%
1-13	1198.7	1289.91	7.61%	54.55%	58.97%	4.43%
1-14	918.599	975.667	6.21%	50.00%	53.16%	3.16%
1-15	1347.34	1406.71	4.41%	48.57%	54.41%	5.84%
<b>Average</b>			<b>14.06%</b>			<b>24.38%</b>
2-1	1463.37	1238.32	-15.38%	55.84%	56.25%	0.41%
2-2	1210.86	1054.66	-12.90%	53.52%	64.10%	10.58%
2-3	715.354	978.258	36.75%	15.79%	54.76%	38.97%
2-4	1041.99	979.997	-5.95%	56.16%	47.37%	-8.80%
2-5	849.195	1249.95	47.19%	0.00%	78.57%	78.57%
2-6	1024.98	1222.59	19.28%	50.65%	67.50%	16.85%
2-7	1101.82	1313.46	19.21%	64.38%	66.67%	2.28%

<b>Instance - Period</b>	<b>NP<sub>s</sub></b>	<b>NP<sub>m</sub></b>	<b>(NP<sub>m</sub> - NP<sub>s</sub>) / NP<sub>s</sub></b>	<b>P<sub>s</sub></b>	<b>P<sub>m</sub></b>	<b>P<sub>m</sub> - P<sub>s</sub></b>
2-8	655.333	948.585	44.75%	0.00%	64.10%	64.10%
2-9	816.013	1194.22	46.35%	46.75%	64.38%	17.63%
2-10	873.319	1036.04	18.63%	46.75%	66.67%	19.91%
2-11	1065.13	1132.1	6.29%	47.95%	62.16%	14.22%
2-12	925.867	1279.1	38.15%	52.24%	72.86%	20.62%
2-13	1548.04	1575.19	1.75%	47.30%	56.16%	8.87%
2-14	796.011	1136.43	42.77%	0.00%	61.73%	61.73%
2-15	1363.28	1294.86	-5.02%	47.22%	52.86%	5.63%
<b>Average</b>			<b>18.79%</b>			<b>23.44%</b>
3-1	785.359	1135.58	44.59%	0.00%	53.01%	53.01%
3-2	1007.23	769.459	-23.61%	51.47%	62.67%	11.20%
3-3	888.644	1116.88	25.68%	0.00%	60.53%	60.53%
3-4	845.218	871.332	3.09%	58.33%	64.86%	6.53%
3-5	1074.58	1236.38	15.06%	38.96%	64.20%	25.24%
3-6	1134.24	1146.87	1.11%	46.67%	67.90%	21.23%
3-7	1109.82	1131.25	1.93%	44.59%	67.57%	22.97%
3-8	956.864	1034.33	8.10%	43.48%	62.82%	19.34%
3-9	1015.75	995.748	-1.97%	55.41%	59.46%	4.05%
3-10	630.849	815.731	29.31%	40.43%	72.73%	32.30%
3-11	845.56	1194.12	41.22%	47.62%	58.44%	10.82%
3-12	1066.75	1224.61	14.80%	26.51%	67.53%	41.03%
3-13	725.252	1031.03	42.16%	0.00%	57.14%	57.14%
3-14	1180.1	915.873	-22.39%	54.05%	57.69%	3.64%
3-15	825.21	1397.39	69.34%	0.00%	61.11%	61.11%
<b>Average</b>			<b>16.56%</b>			<b>28.68%</b>
4-1	1160.95	1044.4	-10.04%	55.41%	65.17%	9.76%
4-2	1125.76	1187.57	5.49%	54.93%	53.85%	-1.08%
4-3	836.824	1049.39	25.40%	0.00%	58.54%	58.54%
4-4	825.868	826.539	0.08%	52.70%	67.12%	14.42%
4-5	750.803	729.823	-2.79%	51.28%	60.76%	9.48%
4-6	846.516	1231.73	45.51%	0.00%	64.00%	64.00%
4-7	901.605	992.768	10.11%	47.95%	64.00%	16.05%
4-8	585.481	1080.47	84.54%	0.00%	58.97%	58.97%
4-9	670.556	986.371	47.10%	0.00%	57.32%	57.32%
4-10	638.129	955.241	49.69%	0.00%	62.03%	62.03%
4-11	958.409	1108.02	15.61%	0.00%	58.90%	58.90%
4-12	1060.55	1011.36	-4.64%	41.10%	63.64%	22.54%
4-13	1028.59	1385.67	34.72%	0.00%	48.72%	48.72%
4-14	819.283	1081.07	31.95%	0.00%	62.67%	62.67%
4-15	1325.73	1317.31	-0.64%	58.11%	58.90%	0.80%
<b>Average</b>			<b>22.14%</b>			<b>36.21%</b>
5-1	697.835	1140.63	63.45%	0.00%	59.49%	59.49%

<b>Instance - Period</b>	<b>NP<sub>s</sub></b>	<b>NP<sub>m</sub></b>	<b>(NP<sub>m</sub> - NP<sub>s</sub>) / NP<sub>s</sub></b>	<b>P<sub>s</sub></b>	<b>P<sub>m</sub></b>	<b>P<sub>m</sub> - P<sub>s</sub></b>
5-2	856.265	962.91	12.45%	49.30%	63.64%	14.34%
5-3	839.98	824.388	-1.86%	40.74%	61.90%	21.16%
5-4	836.957	839.153	0.26%	41.43%	59.72%	18.29%
5-5	903.006	1038.4	14.99%	30.53%	56.58%	26.05%
5-6	875.03	1009.15	15.33%	34.04%	67.11%	33.06%
5-7	935.479	887.617	-5.12%	48.72%	61.25%	12.53%
5-8	531.361	781.901	47.15%	0.00%	53.09%	53.09%
5-9	685.127	928.226	35.48%	0.00%	55.00%	55.00%
5-10	599.299	744.778	24.27%	42.25%	54.67%	12.41%
5-11	607.171	860.834	41.78%	0.00%	60.26%	60.26%
5-12	816.282	1094.51	34.08%	4.00%	66.22%	62.22%
5-13	544.01	907.088	66.74%	0.00%	58.44%	58.44%
5-14	1147.55	1021.22	-11.01%	51.35%	68.00%	16.65%
5-15	830.022	1145.87	38.05%	0.00%	69.86%	69.86%
<b>Average</b>			<b>25.07%</b>			<b>38.19%</b>

## 5.5 Chapter summary

The blooming e-marketing platforms put combinatorial auctions into use in transportation service procurement. As rolling horizon planning concept gradually adopted, carriers need to plan their transportation operations several days in advance, which makes it necessary to consider multiple periods in a combinatorial auction for transportation service procurement. This chapter studies an important subproblem of combinatorial auction, the bid generation problem, in truckload transportation service procurement, with consideration of multi-period and uncertainty of future transportation requests. By applying the scenario approach in stochastic programming, the investigated problem is formulated as a MILP model and solved by a Benders decomposition approach. The performance of the model and the approach is evaluated by numerical experiments on multiple sets of randomly generated instances. The results demonstrate that the Bender decomposition algorithm is much more efficient than CPLEX solver in solving large instances of the problem. This implies that this algorithm has a potential to be used by carriers in a combinatorial auction for transportation service procurement when they adopt a rolling horizon planning approach and want to consider request uncertainty in their operation planning. Our numerical evaluation of the value of considering probabilistic lanes and multi-period in the BGP also shows that it is profitable to take the two features into consideration when solving the BGP for CA.

## 6 Conclusions and perspectives

### 6.1 Conclusions

Truckload transportation accounts for a substantial portion of transportation industry, where shippers procure transportation services from carriers. Transportation service procurement is often realized by combinatorial auctions. The design of combinatorial auction mechanism, as well as the method to solve one of the main decision problems, the bid generation problem, affects the efficiency of a combinatorial auction. Through designing effective auction mechanisms and efficient methods for solving related bid generation problems, both shippers and carriers can save costs and increase profits respectively. After introducing the research background in Chapter 1 and reviewing the related research works in Chapter 2, this thesis studies three problems raised in the procurement of truckload transportation services realized by combinatorial auctions.

In chapter 3, a problem of combinatorial auction for truckload transportation service procurement is studied which involves multiple shippers and carriers to maximize the social efficiency. This problem is equivalent to the one that minimize the total cost of serving all the lanes that need to be outsourced by the shippers. Both centralized approach and decentralized approach to solve this problem are proposed. For the centralized approach, a mixed-integer linear programming model is formulated for the problem and solve by the CPLEX solver. For the decentralized approach, two two-phase combinatorial auction mechanisms are designed, one with supplementary bundles of requests offered for bid generated by the auctioneer and another with supplementary bids generated directly by the carriers in the second phase. The two phases are the clock auction phase and the supplementary bidding phase respectively. Computational results show that compared with single-phase combinatorial clock auction, the proposed two-phase mechanisms show evident advantages in time efficiency and cost savings for the auctioneer. Meanwhile, the social efficiency of the auction's outcome (request allocation) is improved by the mechanisms.

In chapter 4, a bid generation problem of a carrier in a combinatorial auction for truckload transportation service procurement is studied to maximize the net profit of the carrier. In this problem, both pre-exist commitments/contracts (reserved lanes) and the requests (for-bid lanes) that the carrier want to bid for in the auction are

considered. The carrier needs to decide both which lanes to bid for in the combinatorial auction and the routes to serve both the reserved lanes and the selected for-bid lanes. A mixed-integer linear programming model and a set partition model are formulated for the problem. A column generation algorithm is also proposed for the problem with the subproblem (elementary shortest path problem) solved by a dynamic programming based labeling algorithm. Numerical experiments are conducted to compare the solutions obtained by the MILP model solved by the CPLEX solver and the column generation algorithm. The results demonstrate that the proposed algorithm can quickly find a near-optimal solution of the studied problem.

In Chapter 5, the bid generation problem studied in Chapter 4 is extended to one that considers both multiple periods and the uncertainty of requests in truckload transportation service procurement. This stochastic optimization problem is formulated as a mixed integer linear programming model through scenario optimization and deterministic equivalence. To solve this model, a Benders decomposition approach is proposed with Pareto-optimal cut to accelerate the solution process of the approach. Computational results demonstrate that the proposed Benders decomposition approach is much more efficient than CPLEX solver in terms of computation time for solving large instances of the problem. The value of considering uncertain requests and multiple periods in the bid generation is also evaluated by numerical experiments. The results show that considering uncertain requests in advance can improve the net profit of the carrier and considering multiple periods can improve the carrier's competitiveness.

## **6.2 Perspectives for future research**

Although effective auction mechanisms and bid-generation algorithms are proposed to the problems raised in combinatorial auctions for truckload transportation service procurement, there are still many works that can be done to improve these mechanisms and algorithms and to extend the problems studied to more complex environments.

Firstly, for the combinatorial auction mechanisms examined in this thesis, the methods proposed for generating supplementary bundles/bids in the supplementary bidding phase may not be the only way to generate them and introducing the supplementary bidding phase may not be the only way to accelerate the auction process for finding an efficient allocation of requests. Whether there are better methods to improve the efficiency of a combinatorial auction and to accelerate its



process can be an interesting research topic in the future.

Secondly, for the truckload bid generation problem studied in Chapter 4, the proposed column generation algorithm may not obtain a satisfactory solution for some instances of the problem, our future work will focus on improving this algorithm and combining it with branch and bound to devise a branch-and-price method that can optimally solve the problem.

Thirdly, for the bid generation problem considering multi-period and uncertainty in Chapter 5, other ways to accelerate the Benders decomposition approach need to be investigated. In addition, it will be worthy to extend this problem to consider the vehicle depot of the carrier in the bid generation problem, and to find an efficient heuristic algorithm to solve the problem quickly for large instances.

## A Résumé étendu en Français

### A.1 Introduction

Le transport de marchandises joue un rôle important dans la vie économique et sociale. Pour le transport de marchandises, compte tenu de la façon dont les marchandises ou les demandes de transport sont organisées, il existe deux grandes catégories de transport, le transport direct et le transport groupé (Caplice & Sheffi, 2006). Ces deux catégories sont généralement connues sous le nom de transport par camions entiers (TL) et de transport de chargement partiel(LTL). Dans le transport par camions entiers, les marchandises de chaque demande occupent tout l'espace ou la capacité de chaque véhicule. Ce mode de transport de marchandises est généralement choisi lorsqu'un expéditeur a suffisamment de marchandises pour remplir un camion entier, que les marchandises sont urgentes ou que l'expéditeur préfère utiliser un camion dédié pour transporter ses marchandises. L'avantage du transport par camions entiers est que les marchandises peuvent être expédiées directement de l'origine à la destination, ce qui garantit l'efficacité du transport tout en évitant les dommages possibles causés par le chargement et le déchargement répétés des marchandises pendant un processus de transport. Le transport par camions entiers est par opposition au transport de chargement partiel. Dans le cas du transport de chargement partiel, un véhicule peut répondre à plusieurs demandes simultanément. Pendant le service d'une demande, le véhicule peut visiter un autre terminal pour télécharger ou télécharger des marchandises.

Étant donné que le transport par camions entiers occupe environ 70% du transport routier total, cette thèse se concentre sur le transport par camions entiers

Avec le développement continu du marché, les produits et les services poursuivent le raffinement. Les fabricants ou les distributeurs choisissent généralement de sous-traiter les tâches de transport à des entreprises professionnelles. C'est-à-dire que les expéditeurs se procurent des services de transport auprès des transporteurs. Le marché du transport par camions entiers est fragmenté, concurrentiel et fonctionne avec de faibles marges bénéficiaires, ce qui rend l'achat de services de transport important pour les expéditeurs et les transporteurs qui recherchent l'efficacité économique. Pour les expéditeurs, ils veulent maîtriser leurs coûts et offrir un service de haut niveau à leurs clients. Pour les transporteurs, ils souhaitent réduire

les repositionnements de véhicules vides et fonctionner efficacement. Cependant, le camionnage consomme des quantités de carburant ainsi qu'une pollution atmosphérique et sonore. Ainsi, à l'exception de l'efficacité économique individuelle, l'efficacité sociale doit être prise en considération. Dans ce contexte, une méthode raisonnable est nécessaire pour l'achat de services de transport par camions entiers.

Le processus par lequel les expéditeurs achètent des services de transport pour plusieurs demandes de plusieurs transporteurs peut être considéré comme un problème d'allocation (Lim et al., 2008). En d'autres termes, les expéditeurs attribuent leurs demandes de transport à un groupe de transporteurs. L'attribution de ces demandes peut être réalisée par une approche centralisée ou une approche décentralisée. L'approche centralisée, qui repose sur un modèle de programmation mathématique centralisé, nécessite la révélation d'informations confidentielles sur les coûts des transporteurs et est donc peu pratique. L'approche décentralisée, quant à elle, est un jeu entre chargeurs et transporteurs et qui comprend de nombreux mécanismes différents. Parmi les différentes approches décentralisées, l'enchère combinatoire (CA) est stratégique sur le marché en plein essor du camionnage électronique (Caplice, 2007; Caplice & Sheffi, 2006).

L'enchère combinatoire est un mécanisme représentatif basé sur l'enchère pour l'achat de services de transport qui permet aux transporteurs de soumissionner pour plusieurs demandes à la fois, tandis que l'enchère à un seul article n'autorise qu'une seule demande dans l'offre. Cette caractéristique augmente l'efficacité de l'enchère, puis rend l'enchère combinatoire de plus en plus populaire (Abrache et al., 2007; De Vries & Vohra, 2003). Dans les enchères combinatoires, le commissaire-priseur est au nom des expéditeurs, et les enchérisseurs sont les transporteurs qui souhaitent servir les demandes de transport des expéditeurs. Pour les transporteurs, l'un des avantages des enchères combinatoires par rapport à l'approche centralisée est qu'ils n'ont pas besoin de révéler leurs données commerciales telles que les contrats existants, les coûts de transport pour répondre aux appels d'offres et le nombre de véhicules. Étant donné que l'enchère combinatoire joue un rôle important dans l'achat de services de transport, le mécanisme de chaque enchère combinatoire doit être bien conçu pour atteindre l'efficacité.

Sur la base du nombre de tours traités dans CA, les mécanismes de CA conçus peuvent être classifiés en CA à un seul tour et CA à plusieurs tours (CA itérative). Une enchère combinatoire à un tour ne traite l'enchère qu'une seule fois tandis qu'une

enchère combinatoire itérative itère le processus d'enchère combinatoire à un tour jusqu'à ce que certaines conditions d'arrêt soient satisfaites. La routine simplifiée de CA à tour unique dans l'achat des services de transport peut être décrite comme suit. Le commissaire-priseur représentant le ou les expéditeurs fournit un ensemble de demandes de transport avec des prix d'externalisation dans le pool d'enchères.

1) Les enchérisseurs (transporteurs) soumettent au commissaire-priseur leurs enchères pour un ensemble de demandes basées sur les informations de la demande afin de maximiser leurs profits.

2) Le commissaire-priseur trouve une allocation optimale des demandes aux enchérisseurs pour minimiser son coût, c'est-à-dire déterminer les gagnants des enchères.

Deux problèmes majeurs doivent être résolus dans le processus d'enchères. Le premier est généralement appelé problème de génération d'enchères (BGP), c'est-à-dire que chaque opérateur génère son offre en sélectionnant les demandes à inclure dans son offre groupée (bid). Le second est le problème de détermination des gagnants, dans lequel le commissaire-priseur détermine les gagnants des enchères soumises par tous les enchérisseurs.

Cette thèse est consacrée à l'étude des problèmes d'enchères combinatoires pour l'achat de services de transport par camions entiers, tant du point de vue global qu'individuel. D'un point de vue global, la conception du mécanisme d'enchères est étudiée en tenant compte de l'efficacité sociale. Et du point de vue individuel, l'un des problèmes majeurs, le problème de génération d'enchères dans les enchères combinatoires de contexte différent est étudié dans un souci d'efficacité économique du transporteur unique. Avec ces considérations, certains problèmes sont remarqués dans les enchères combinatoires.

Premièrement, en raison de la nature décentralisée des enchères combinatoires, il est très difficile d'attribuer toutes les demandes dans le pool d'enchères d'un coup. Dans ce contexte, une enchère combinatoire multi-tours émerge pour résoudre ce problème. Une enchère combinatoire à plusieurs tours est que le processus d'enchère itère plusieurs tours pour rechercher une meilleure allocation. Cependant, sans partage d'informations entre les transporteurs, les demandes du groupe de chaque transporteur peuvent se chevaucher, c'est-à-dire que certaines demandes sont mises en concurrence par plusieurs transporteurs, tandis que d'autres ne font l'objet d'une offre par aucun transporteur. De telles enchères combinatoires sont souvent arrêtées avec une

allocation inefficace, qui ne parvient pas à procurer des services pour toutes les demandes. Même obtenir une allocation efficace, une telle enchère peut prendre un grand nombre de tours.

Deuxièmement, en tant que grands fournisseurs de services de transport, le mode de fonctionnement des transporteurs de lots complets peut influencer l'efficacité de l'ensemble du système logistique. Dans les enchères combinatoires à plusieurs tours, le problème de génération d'enchères de chaque transporteur est crucial car il est à la base du problème de détermination des gagnants et peut influencer l'ajustement des prix d'externalisation des demandes au tour suivant. Étant donné que tous les transporteurs sont axés sur le profit, les demandes pour lesquelles ils ont choisi de soumissionner doivent être celles qui peuvent leur apporter le plus de profit. Une demande sera choisie par un transporteur soit qu'il puisse combler le repositionnement du véhicule vide soit que le revenu de servir cette demande dépasse le coût du trajet supplémentaire. Ainsi, le problème de génération d'enchères est généralement une variante du problème de tournée de véhicules. Ce problème est NP-difficile et difficile à résoudre dans un temps raisonnable pour les problèmes à grande échelle.

Troisièmement, le marché du transport par camions entiers est très concurrentiel, ce qui oblige les transporteurs à saisir les opportunités futures dans les services de transport. Pour atteindre cet objectif, lorsqu'un transporteur planifie ses opérations de transport, il doit considérer non seulement ses demandes de transport actuelles mais aussi les demandes qu'il pourrait acquérir à l'avenir. Comme l'ont souligné Wang et al. (2014) and Wang and Kopfer (2015), l'hypothèse selon laquelle les transporteurs en tant qu'enchérisseurs dans une vente aux enchères ne sont autorisés à concourir que pour les demandes de transport disponibles dans la période actuelle est plutôt restrictive. Une enchère plus efficace doit être menée selon un horizon glissant qui prend en compte plusieurs périodes (jours) dans l'allocation de sa demande. De plus, certaines demandes peuvent émerger dans les périodes futures mais ne peuvent être prévues dans la période en cours. La prise en compte ou non de ces demandes futures dans le problème de génération d'enchères aura un impact significatif sur l'efficacité de l'enchère sur le long terme.

Cette thèse a étudié trois problèmes qui visent à fournir une solution optionnelle à chacun des problèmes mentionnés ci-dessus, ainsi que des informations managériales aux acteurs du marché du transport par camions entiers. L'un des problèmes se concentre sur la conception de mécanismes de CA pour l'achat de

services de transport par camions entiers, tandis que les deux autres se consacrent à la résolution d'un problème principal, le problème de génération d'enchères, dans le processus de CA.

(1) Conception d'un mécanisme d'enchères combinatoires à plusieurs tours en deux phases avec des faisceaux supplémentaires de demandes de paquet d'enchères générées par le commissaire-priseur et les transporteurs respectivement dans la deuxième phase. Chaque étape du mécanisme conçu est formulée avec un modèle de programmation linéaire en nombres entiers (MILP). Des expériences informatiques sont menées avec des instances générées aléatoirement de différentes tailles de problème ainsi qu'une proportion différente du nombre de tours de l'enchère au cadran dans le total des tours de CA. Par rapport à la vente aux enchères à horloge monophasée, les mécanismes à deux phases conçus présentent des avantages évidents en termes d'efficacité du temps et d'économies pour le commissaire-priseur. Parallèlement, l'efficacité sociale du résultat de l'enchère (allocation des demandes) est améliorée par les deux mécanismes.

(2) Problème de génération d'enchères d'un seul transporteur dans le mécanisme d'enchères conçu. Étant donné que le modèle MILP de ce problème ne peut pas obtenir une solution optimale à grande échelle de problème en un temps raisonnable, un algorithme de génération de colonnes est proposé pour résoudre le problème apparu dans l'enchère combinatoire. Des expériences numériques d'instances générées aléatoirement démontrent que l'algorithme proposé peut rapidement trouver une solution quasi optimale du problème étudié.

(3) Problème de génération d'enchères compte tenu des périodes multiples et de l'incertitude dans l'achat des services de transport par camions entiers. Ce problème d'optimisation stochastique est formulé comme un modèle de programmation linéaire en nombres entiers mixtes via l'optimisation de scénarios et l'équivalence déterministe. Pour résoudre le modèle, une approche de décomposition de Benders est proposée. Les résultats de calcul avec des instances générées aléatoirement et réalistes démontrent que l'approche de décomposition de Bender est beaucoup plus efficace que le solveur CPLEX en termes de temps de calcul pour résoudre de grandes instances du modèle. La valeur de la prise en compte des demandes incertaines et des périodes multiples dans la génération des enchères est également évaluée par des expériences numériques.

## A.2 Revue de littérature

L'achat en services de transport de marchandises correspond aux besoins de transport des expéditeurs et aux capacités des transporteurs. Au cours des dernières décennies, le développement du commerce électronique facilite le développement du transport de marchandises, des marchés en ligne pour l'achat de services de transport de marchandises apparaissent en nombre, tels que FreightMatrix, Freight-traders et logistics.com. Le marché électronique facilite la connexion et la collaboration entre les chargeurs et les transporteurs. Une variété de cadres ou de mécanismes sont utilisés par différentes places de marché électroniques, les littératures les classent généralement en trois grandes catégories : les enchères, les catalogues et les échanges (négociations), tandis que les modes d'approvisionnement peuvent être des contrats à long terme et des marchés au comptant. Selon la littérature, le mécanisme basé sur les enchères est largement utilisé dans l'achat en services de transport.

Le mécanisme d'enchères joue un rôle important dans l'achat en services de transport, de nombreux mécanismes d'enchères différents peuvent être trouvés dans des travaux de recherche antérieurs, par exemple, les enchères d'un article, les enchères combinatoires et les enchères doubles. Cette thèse porte sur l'étude des enchères combinatoires pour l'achat en services de transport par camions entiers.

L'enchère combinatoire (CA) est proposée pour la première fois par Rassenti et al. (1982) pour l'attribution des créneaux d'atterrissage aux aéroports. CA permet aux soumissionnaires de placer des offres sur des combinaisons d'articles plutôt que sur des articles individuels. Ce mécanisme a exprimé les synergies entre les ensembles de biens ou de services, ce qui a le potentiel de réduire les coûts et d'augmenter l'efficacité (Lunander & Lundberg, 2013). De nombreux travaux ont apporté des connaissances théoriques et pratiques pour la conception de CA (Abrache et al., 2004; Bichler et al., 2009; De Vries & Vohra, 2003; Pekeč & Rothkopf, 2003). À l'exception de l'approvisionnement en services de transport, CA est également adoptée par de nombreux environnements industriels différents tels que la coordination des robots, l'échange de permis de pollution, la planification de la fabrication, la restauration des repas scolaires, etc. (Berhault et al., 2003; Epstein et al., 2004; Kutanoglu & Wu, 1999; Leyton-Brown et al., 2000).

Il existe de nombreux mécanismes de CA différents (Cramton et al., 2006), certains d'entre eux sont bien adoptés par les chercheurs et les praticiens. Le mécanisme de Vickrey-Clarke-Groves (VCG) (L. Ausubel & Milgrom, 2006) est un

mécanisme de CA dans lequel les soumissionnaires déclarent leurs évaluations pour tous les packages. Les articles sont alloués efficacement pour maximiser la valeur totale. Chaque gagnant paie le coût d'opportunité de ses gains : la valeur incrémentale est dérivée en attribuant les articles de l'enchérisseur en fonction de leur prochaine meilleure utilisation. L'enchère au cadran (L. Ausubel et al., 2006) est un mécanisme de CA itératif dans lequel le commissaire-priseur annonce les prix des articles, et les enchérisseurs indiquent les quantités de chaque article. Les prix des articles avec une demande excédentaire seront ajustés, puis chaque enchérisseur exprimera les quantités aux nouveaux prix. L'environnement de sélection d'utilisateurs adaptatif progressif (PAUSE) (Kelly & Steinberg, 2000; Land et al., 2006) est un mécanisme de CA maniable par le calcul dans lequel le commissaire-priseur n'est pas confronté au problème de détermination du gagnant. La responsabilité d'évaluer une offre combinatoire est transférée au soumissionnaire qui fait l'offre.

Comme le CA conventionnelle, les mécanismes de CA conçus pour TSP dans les travaux peuvent également être triés en CA à un tour (one-shot) et en CA à plusieurs tours (itérative). Il est rapporté que lorsque Sears Logistics Services a utilisé la combinatoire, il a choisi une version itérative de l'enchère d'approvisionnement avec des offres scellées. Dans cette enchère itérative, les enchères se déroulent en plusieurs tours. L'enchère combinatoire itérative est également appelée enchère combinatoire à plusieurs tours de nos jours. Par rapport à le CA à un tour, CA à plusieurs tours présente deux avantages. La première est que le CA multi-tours peut simplifier la génération d'enchères des enchérisseurs en fournissant des informations sur les prix de chaque demande ou de chaque groupe de demandes à chaque tour. L'autre avantage est que le CA à tours multiples fournit un processus de découverte des prix aux enchérisseurs, ce qui permet aux enchérisseurs de soumettre des offres plus pertinentes pour maximiser l'efficacité sociale de l'enchère. Certains chercheurs ont étudié le CA à un tour (R. L.-Y. Chen et al., 2009; W. Elmaghraby & Keskinocak, 2000; Wedad Elmaghraby & Keskinocak, 2004; Song & Regan, 2003; Srivastava et al., 2008), tandis que d'autres ont étudié le CA à plusieurs tours (Day & Raghavan, 2008; Kwon et al., 2005; Tian et al., 2011; D. Wang & Wang, 2015). À l'exception des enchères combinatoires, d'autres mécanismes d'enchères courants incluent la double enchère, l'enchère séquentielle et les mécanismes d'échange basés sur l'enchère.

Le problème de génération d'enchères (BGP) est un problème de décision clé en CA, qui est généralement résolu par les transporteurs. Ce problème se concentre sur la



sélection et le regroupement des demandes à soumettre dans CA. BGP est également reconnu comme un problème de construction d'enchères, un problème de génération de paquets ou un problème de regroupement de demandes. De nombreux travaux de recherche ont contribué à ce problème en CA pour l'achat de services de transport. Selon qu'il existe des facteurs stochastiques lors de la résolution du problème, un BGP peut être déterministe ou stochastique.

Dans les problèmes de génération d'enchères déterministes, selon que le BGP considère plusieurs périodes de décision, le problème peut être divisé en BGP à période unique et BGP à plusieurs périodes. Le BGP à période unique est étudié dans la plupart des cas (Chang, 2009; Gansterer & Hartl, 2018; Lee et al., 2007; Song & Regan, 2005; Xiubin Wang & Xia, 2005; Yan et al., 2018), tandis que le BGP à périodes multiples est rarement considéré (E Mamaghani et al., 2019a; E. Mamaghani et al., 2019b). BGP stochastique peuvent être trouvés dans (Hammami et al., 2020; Hammami et al., 2021; Kuyzu et al., 2015; Triki et al., 2014).

Dans les enchères combinatoires pour TSP, le problème de génération d'enchères d'un transporteur doit généralement prendre en compte les synergies entre les nouvelles demandes acquises et les demandes préexistantes pour réduire le repositionnement des véhicules vides et augmenter les profits. Ainsi, les problèmes de génération d'enchères pour TSP sont généralement pris en compte lors de la planification des itinéraires.

Le mode de transport de marchandises étudié dans cette thèse est le transport par camions entiers (TL). Le transport de chargements complets est sans escale, c'est-à-dire que lorsqu'un véhicule répond à une demande de chargements complets, il se rend directement de son origine à sa destination sans visiter aucun autre terminal. L'unité de base d'une demande de chargement de camion est généralement appelée une voie. De nombreux chercheurs se sont consacrés à l'étude de la planification des itinéraires pour le transport TL, y compris le problème de tournée des véhicules, le problème de couverture de voie et la planification de l'horizon glissant.

Certains résultats de la revue de la littérature sont présentés ci-dessous. Premièrement, les marchés électroniques du transport de marchandises prospèrent avec la prospérité des commerçants électroniques. Les mécanismes basés sur les enchères sont principalement utilisés pour l'achat de services de transport. Parmi les différents mécanismes, l'enchère combinatoire est bien adoptée à la fois par les universitaires et les praticiens industriels. Différents mécanismes d'enchères

combinatoires ont été conçus avec un contexte et des contraintes spécifiques. L'enjeu majeur dans la conception des mécanismes de CA est d'assurer à la fois l'efficacité du temps et de la solution, qui sera longtemps la préoccupation des chercheurs. Deuxièmement, le problème de génération d'enchères en tant que problème de décision majeur dans le CA pour TSP a attiré l'attention de nombreux chercheurs, différentes stratégies de regroupement et de tarification ont été conçues. Cependant, la plupart des études se sont concentrées sur le BGP déterministe alors que les études sur le BGP stochastique n'ont porté que sur les prix stochastiques des requêtes. De plus, en raison de sa complexité de calcul, des algorithmes efficaces sont toujours nécessaires pour les problèmes à grande échelle. Troisièmement, en général, les problèmes de routage ont été pris en compte dans la littérature pour regrouper les requêtes/voies. La couverture de voie soulevée dans le cadre d'une collaboration logistique est devenue de plus en plus populaire dans l'achat de services de transport par camion, ce qui peut être facile à étendre au BGP pour le TSP par camion avec des caractéristiques différentes. Enfin, une stratégie de planification avec des horizons mobiles est devenue publique car elle est plus proche de l'application pratique et offre plus de choix aux transporteurs pour obtenir de meilleures opérations, mais BGP avec un facteur à la fois stochastique et dynamique n'a pas encore été pris en compte. Le travail de cette thèse est réalisé sur la base de ces résultats.

### **A.3 Mécanismes d'enchères combinatoires en deux phases avec des paquets de demandes supplémentaires**

Ce chapitre étudie un problème soulevé dans l'achat en services de transport par camions entiers impliquant un ou plusieurs expéditeurs et plusieurs transporteurs. Dans le problème de l'achat de services de transport (TSP) considéré, un ou plusieurs expéditeurs ont un ensemble de demandes de transport par camions entiers à sous-traiter à un ensemble de transporteurs. Chaque demande de chargement complet est représentée par une voie avec une origine et une destination dans un réseau de transport. Chaque transporteur impliqué dans le TSP dispose d'une flotte de véhicules initialement située dans son propre dépôt de véhicules. Chaque véhicule doit quitter et retourner à son propre dépôt avant et après avoir desservi les voies qui lui sont attribuées. Le temps de service de chaque véhicule est limité et un coût fixe est encouru si un véhicule dessert une tournée. Le revenu pour desservir chaque voie est donné, qui est indépendant de la répartition des bénéfices/coûts entre les expéditeurs

et les transporteurs impliqués.

Le problème est considéré du point de vue de l'efficacité sociale. L'objectif est de minimiser la distance totale de déplacement/le coût des véhicules/transporteurs pour desservir toutes les demandes (voies), ce qui fait référence à la consommation de carburant ou à la pollution de l'air de toutes les tournées pour servir les demandes. C'est-à-dire que la maximisation de l'efficacité sociale équivaut à la minimisation du coût total de transport pour desservir toutes les voies.

Lors de la formulation du problème, les voies réservées aux offres contiennent toutes les voies que les expéditeurs souhaitent sous-traiter aux transporteurs. Si un transporteur souhaite acquérir une ou plusieurs voies interdites à l'enchère, sauf pour sélectionner les voies à enchérir, il doit également construire ses itinéraires de véhicules pour desservir ces voies. Chaque véhicule d'un transporteur dessert une seule tournée avec des demandes. Le problème est un problème de tournées de camions multi-dépôts (multi-transporteurs) avec des coûts fixes et une contrainte de durée maximale.

Les approches centralisées et décentralisées sont étudiées dans ce chapitre. D'une part, un modèle de programmation de ligne à nombres entiers mixtes est formulé pour le problème d'achat en services de transport résolu en utilisant une approche centralisée. En revanche, motivée par l'enchère clock-proxy proposée par Ausubel et al. (2006), deux mécanismes de CA multi-tours à deux phases sont proposés pour résoudre le même problème. L'enchère au chronomètre combine la découverte simple et transparente des prix de l'enchère au chronomètre avec l'efficacité de l'enchère par procurement.

Comme dans l'enchère par proxy d'horloge, la deuxième phase de nos mécanismes CA proposés est également utilisée pour améliorer l'efficacité de l'allocation des demandes. Notre objectif est de trouver une stratégie de regroupement efficace pour la deuxième phase de CA, qui puisse accélérer le processus de CA avec de meilleurs résultats. Dans les mécanismes de CA en deux phases proposés, la première phase est une enchère au rythme combinatoire, dans laquelle le commissaire-priseur augmente le prix d'une demande (voie) si aucun opérateur n'enchérit pour cette demande. Chaque transporteur génère son offre sur la base des prix de toutes les demandes ouvertes aux enchères à chaque tour. La deuxième phase vise principalement à vendre les demandes restantes (voies) après la première phase en générant des faisceaux supplémentaires de demandes ouvertes aux enchères. Les

deux mécanismes de CA génèrent respectivement des lots supplémentaires par le commissaire-priseur et les transporteurs. Dans le cas où le commissaire-priseur génère des lots supplémentaires, chaque transporteur décide s'il enchérit pour un ou plusieurs lots supplémentaires. Dans le cas où les transporteurs génèrent des lots supplémentaires, chaque transporteur génère et offre des lots de demandes sur la base des résultats du dernier tour de CA. Les tarifs de desserte des forfaits supplémentaires pourront également être ajustés au cours de la deuxième phase. À notre connaissance, il s'agit d'une nouvelle variante de CA pour l'achat en services de transport de transport par camions entiers.

Le processus du mécanisme en deux phases est illustré dans les figures suivantes. Les résultats des calculs sur des instances générées aléatoirement montrent que les mécanismes proposés peuvent obtenir une allocation optimale ou quasi-optimale avec un écart inférieur à 3% pour les instances testées. De plus, les mécanismes de CA en deux phases peuvent aider le commissaire-priseur à réduire les coûts d'achat tout en améliorant l'efficacité sociale.

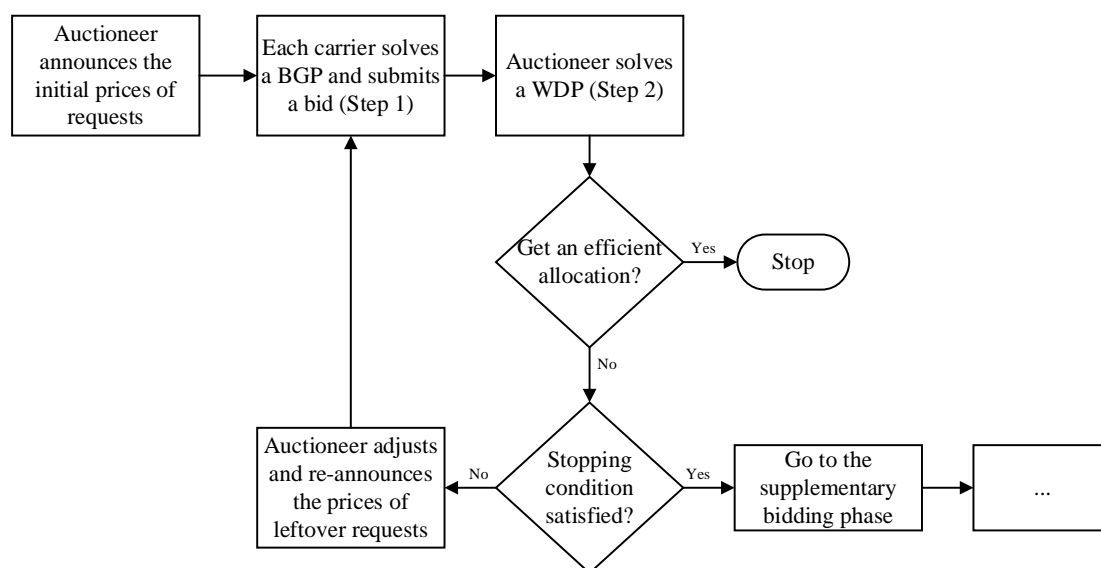


Figure A-1 Phase d'enchères à l'cadran

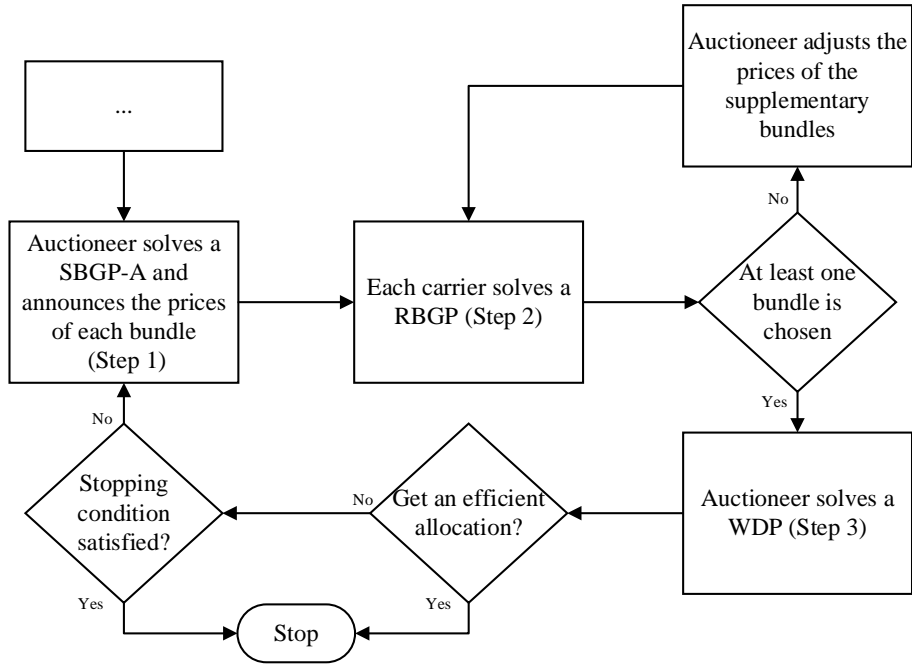


Figure A-2 Phase d'enchère supplémentaire avec des lots supplémentaires générés par le commissaire-priseur

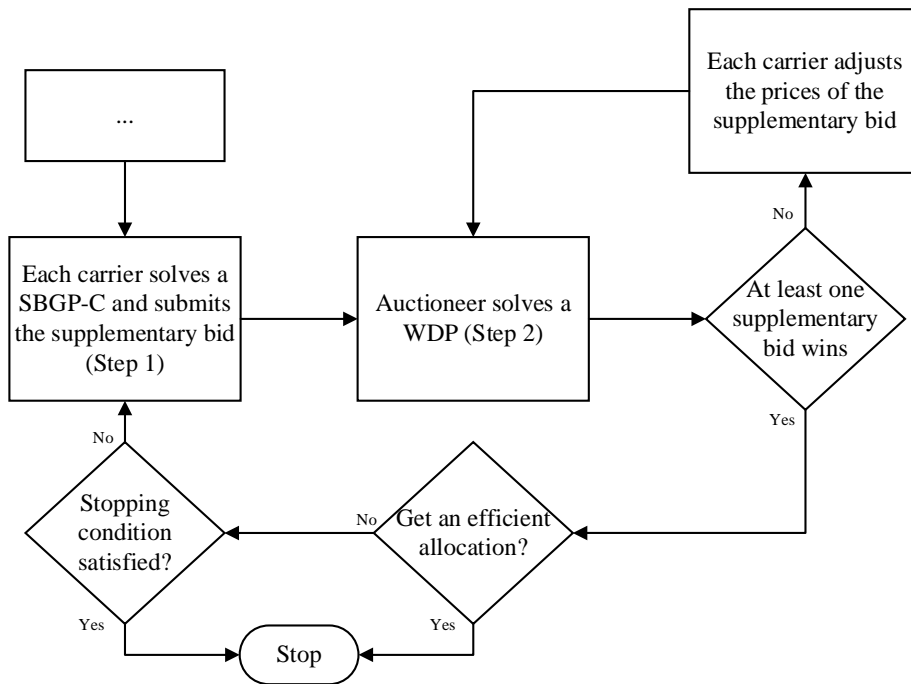


Figure A-3 Phase d'enchère supplémentaire avec des paquet supplémentaires générées par le transporteur

#### **A.4 Algorithme de génération de colonnes pour un problème de génération d'enchères**

Dans le chapitre 3, les mécanismes de CA pour la TSP sont étudiés. Ce chapitre se concentre ensuite sur l'un des principaux problèmes de décision des mécanismes de CA, le problème de génération d'enchères, du point de vue d'un transporteur. Le BGP considéré au chapitre 3 ne considère que les demandes (voie) à soumissionner par le transporteur. Cependant, dans un cas général, avant de participer à CA, le transporteur a généralement des engagements préexistants. Ces engagements peuvent provenir des contrats à long terme entre les expéditeurs et le transporteur ou des anciennes enchères. Par conséquent, lorsqu'il participe à une nouvelle CA, le transporteur doit tenir compte à la fois des engagements préexistants et des demandes qu'il peut obtenir de cette CA. Ci-après, les demandes (voie) dans les engagements préexistants et dans CA sont respectivement appelées voies réservées et voies interdites. La différence entre les deux types de voies est que les voies réservées doivent être desservies par le transporteur tandis que les voies interdites peuvent être sélectionnées. En effet, le transporteur participe généralement à CA pour obtenir des voies d'interdit en complément des voies réservées soit pour réduire le repositionnement de véhicules vides, soit pour rechercher plus de profit. Dans tous les cas, le transporteur devra reconstituer ses itinéraires de véhicules, ce qui concatène le BGP avec le problème de tournées de véhicules.

Dans le problème de génération d'enchères étudié, un transporteur qui participe à CA pour le TSP détenu par les expéditeurs souhaite générer une offre avec une ou plusieurs demandes de chargements complets dans le pool d'enchères. Chaque demande de chargement complet est représentée par une voie avec une origine et une destination dans un réseau de transport symétrique. Avant de participer à CA, le transporteur dispose d'un ensemble de voies réservées qu'il doit desservir. Dans CA, si le transporteur souhaite se procurer des voies interdites, sauf pour sélectionner les voies à soumissionner, il doit également reconstituer ses itinéraires de véhicules pour inclure ses voies interdites sélectionnées en plus de ses voies réservées.

Le transporteur dispose d'une flotte de véhicules initialement située dans son dépôt de véhicules dont le nombre de véhicules est limité. Chaque véhicule du transporteur doit quitter et retourner à son dépôt avant et après avoir desservi les voies qui lui sont attribuées. Chaque véhicule du transporteur ne dessert qu'un seul tour avec des demandes. Le temps d'entretien de chaque véhicule est limité.

La principale contribution de ce chapitre est sous deux aspects.

Premièrement, un modèle MILP et un modèle de partition d'ensemble sont proposés pour le BGP. Dans lequel le modèle de partition du problème est formulé comme suit:

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**Ensembles et indices:**

$R$ , ensemble de tous les route élémentaires possibles

$A_r$ , ensemble de tous les arcs parcourus par le véhicule en cours de route  $r$

**Paramètres:**

$$a_{l,r} = \begin{cases} 1, & \text{si voie } l \text{ est dans route } r \\ 0, & \text{sinon} \end{cases}; l \in A, r \in R$$

$C_l$ , le coût de visite de la voie  $l$ ,  $l \in A$

$P_l$ , le revenu de visite de la voie  $l$ ,  $l \in A$

**Variables de decision:**

$$x_r = \begin{cases} 1, & \text{si route } r \text{ est selectionn} \\ 0, & \text{sinon} \end{cases}; r \in R$$

---

Model *BGP-SP*

$$Max \sum_{r \in R} \sum_{l \in A_r} (P_l - C_l) a_{l,r} x_r$$

s.t.

$$\sum_{r \in R} a_{l,r} x_r = 1; l \in L_r \tag{A-1}$$

$$\sum_{r \in R} a_{l,r} x_r \leq 1; l \in L_b \tag{A-2}$$

$$\sum_{r \in R} x_r \leq H \tag{A-3}$$

$$x_r \in \{0, 1\}, r \in R \tag{A-4}$$

La fonction objectif est toujours de maximiser le profit net du transporteur. Le bénéfice net est la différence entre les recettes et le coût de la desserte des voies des itinéraires. La contrainte (A-1) garantit que chaque voie réservée n'est desservie qu'une seule fois, tandis que la contrainte (A-2) indique que toute voie interdite peut être desservie à plus une fois par le transporteur. La contrainte (A-3) garantit que les véhicules utilisés ne dépassent pas le nombre limite de véhicules. La contrainte (A-4)

limite la plage de valeurs de la variable binaire  $x_r$ .

Deuxièmement, un algorithme de génération de colonnes est proposé pour résoudre la relaxation linéaire du problème basé sur le modèle de partition. Dans l'algorithme de génération de colonnes, une heuristique d'insertion gloutonne est proposée pour construire la solution initiale du problème maître restreint, et deux approches sont proposées pour résoudre le sous-problème, qui sont l'algorithme de programmation dynamique avec étiquetage et l'algorithme de recherche locale.

Dans le modèle de partition, la prise en compte simultanée de tous les éléments (routes) de cet ensemble peut être inabordable en termes de calcul dans la pratique. L'algorithme de génération de colonnes peut ensuite être appliqué pour fournir un processus progressif d'introduction des routes dans le modèle.

La génération de colonnes est un algorithme efficace pour résoudre de grands programmes linéaires. Le principal avantage de la génération de colonnes est qu'il n'est pas nécessaire d'énumérer toutes les possibilités. L'idée de base de la génération de colonnes est de d'abord formuler le problème comme un problème maître restreint avec peu de variables, puis un sous-problème est résolu pour ajouter une nouvelle colonne au problème maître restreint. Le problème maître restreint est le problème d'origine avec seulement un sous-ensemble de variables considéré. La solution du problème maître restreint est une solution réalisable au problème d'origine. Le sous-problème est un problème pour identifier une colonne à ajouter au problème maître restreint. La nouvelle colonne est trouvée en calculant le coût réduit par rapport aux variables duales courantes. Généralement, la colonne qui minimise le coût réduit, ce qui signifie que l'ajout de cette colonne peut améliorer au maximum la solution actuelle, est ajoutée au problème maître restreint.

Dans l'algorithme de génération de colonnes proposé, une heuristique d'insertion gloutonne est conçue pour générer la solution initiale, qui insère d'abord les voies réservées puis les voies interdites. La règle est d'insérer une voie avec une augmentation maximale du profit net à l'itinéraire par rapport à la contrainte de durée maximale.

Dans l'algorithme d'étiquetage, une étiquette  $L_i = \{S_i, d_i, c_i, U_i, n_i\}$  est définie avec la liste de séquences  $S_i$  des requêtes visitées, l'heure de départ  $d_i$  après avoir servi la requête courante  $i$ , le coût cumulé  $c_i$ , l'ensemble des requêtes inaccessibles  $U_i$  et le nombre de requêtes inaccessibles  $n_i$ . Ici, une requête est reconnue comme inaccessible si elle a déjà été servie dans la route partielle jusqu'à l'étape en cours ou que servir la



requête provoquera la violation de la contrainte de durée maximale. L'étiquette s'étendra  $L_i = \{S_i, d_i, c_i, U_i, n_i\}$  à  $L_j = \{S_j, d_j, c_j, U_j, n_j\}$  si la requête  $j$  est ajoutée à la route. Mais avant d'ajouter la requête  $j$ , il faut d'abord vérifier s'il s'agit d'une requête inaccessible. S'il peut être ajouté à la route, soit  $i^+$  le nœud d'origine et  $i^-$  le nœud de destination de la requête  $i$ , alors

$$S_j = S_i \leftarrow j \quad (\text{A-5})$$

$$d_j = d_i + t_{i^-,j^+} + t_{j^+,i^-} \quad (\text{A-6})$$

$$c_j = c_i + c_{i^-,j^+} + c_{j^+,i^-} \quad (\text{A-7})$$

$U_j$  et  $n_j$  seront également mis à jour après vérification du nœud d'origine des requêtes restantes et de la contrainte de durée maximale. Notez que si la demande  $j$  est la première demande après avoir quitté le dépôt, alors  $d_j = t_{D,j^+} + t_{j^+,D}$ ,  $c_j = c_{D,j^+} + c_{j^+,D}$ , où  $D$  désigne le nœud du dépôt. Ou si l'indice  $j$  est le dépôt où l'itinéraire se terminera, alors  $d_j = d_i + t_{i^-,D}$ ,  $c_j = c_i + c_{i^-,D}$ .

Dans le graphique, il peut ne pas y avoir qu'un seul itinéraire du dépôt à la demande  $j$ . Pour les labels  $L_j^1$  et  $L_j^2$  associés à la requête  $j$ , label  $L_j^1$  domine label  $L_j^2$  si

$$d_j^1 \leq d_j^2, c_j^1 \leq c_j^2, U_j^1 \subseteq U_j^2, n_j^1 \leq n_j^2 \quad (\text{A-8})$$

L'algorithme d'étiquetage présenté dans la dernière sous-section prend du temps lorsque le nombre de requêtes est important et que la durée maximale de chaque route est importante, il n'est donc pas adapté aux grandes instances du BGP considéré. Des méthodes heuristiques sont généralement proposées pour résoudre approximativement les ESPPRC apparus dans les algorithmes de génération de colonnes pour divers problèmes de tournées de véhicules. Une méthode heuristique est, au lieu de résoudre un problème de plus court chemin élémentaire, un problème de plus court chemin qui permet à certains nœuds visités plus d'une fois dans un chemin partiel (route) est considéré, mais la relaxation de la contrainte selon laquelle chaque nœud est visité par un chemin partiel (route) au plus une fois dégradera la limite inférieure du modèle de partition d'ensemble correspondant trouvé par la génération de colonnes. Pour cette

raison, nous proposons un algorithme de recherche locale pour résoudre le sous-problème.

Dans l'algorithme de génération de colonnes, après avoir résolu le problème double du problème maître restreint, le coût réduit de chaque route dans le pool de routes (colonne) peut être calculé. L'algorithme de recherche locale essaie d'améliorer certains itinéraires avec un coût réduit nul dans le pool d'itinéraires de sorte que les itinéraires avec un coût réduit négatif puissent être trouvés et entrer dans le pool de colonnes. Cet algorithme applique les trois opérateurs de recherche locale suivants :

(1) Supprimer une demande (voie). Pour une route donnée, cet opérateur supprime une requête dont la suppression réduira au maximum le coût réduit de la route parmi toutes les requêtes amovibles.

(2) Insérer une demande (voie). Pour une route donnée, cet opérateur insère une requête dont l'insertion réduira au maximum le coût réduit de la route parmi toutes les requêtes insérables et reconstruit la route en insérant la requête dans sa meilleure position qui minimise le coût réduit. A noter que dans l'ESPPRC considéré, certaines voies sont associées à un coût négatif (distance), donc l'insertion d'une demande (voie) peut réduire le coût réduit de l'itinéraire.

(3) Supprimer et insérer une demande (voie). Pour une route donnée, cet opérateur retire d'abord une demande de la route puis réinsère cette demande (dans une autre position) ou insère une autre demande dans la route. La combinaison de la demande de suppression et de la demande d'insertion est choisie de telle sorte que le coût réduit de la route soit réduit au maximum après cette opération de suppression/insertion de demande.

L'algorithme de recherche locale peut trouver de nombreuses routes avec un coût réduit nul à améliorer en une seule itération. Ainsi, par rapport à l'algorithme d'étiquetage qui ajoute une seule route au problème maître restreint avec un coût réduit au minimum à chaque itération de l'algorithme de génération de colonnes, l'algorithme de recherche locale consiste à améliorer plusieurs routes dans le problème maître restreint. Pour chaque itinéraire, le processus d'amélioration se répète jusqu'à ce que le coût réduit de l'itinéraire ne puisse plus être amélioré.

## **A.5 Modèle et algorithme de décomposition de Benders pour un problème de génération d'enchères prenant en compte plusieurs périodes et l'incertitude de demandes**

L'achat en services de transport (TSP) est souvent réalisé par enchères combinatoires (CA). Mais le marché des services de transport est féroce et concurrentiel. Pour survivre dans cette concurrence entre les transporteurs et rechercher plus de profits, les transporteurs doivent faire preuve de prévoyance lorsqu'ils participent à CA et élaborent des plans d'exploitation. C'est-à-dire que lorsqu'un transporteur planifie ses opérations de transport, il doit considérer non seulement ses demandes de transport actuelles mais aussi les demandes de transport qu'il pourrait acquérir à l'avenir. Ces dernières années, avec le concept de planification à horizon glissant adopté en logistique, les transporteurs planifient généralement leurs opérations de transport plusieurs périodes (jours) à l'avance. Cela implique que les transporteurs doivent considérer plusieurs périodes lorsqu'ils participent à CA organisée par les expéditeurs. Étant donné que les demandes de transport à l'avenir ne peuvent pas être prévues, les transporteurs doivent tenir compte de l'incertitude des demandes dans de telles enchères.

Pour chaque transporteur, pour s'adapter à la nouvelle tendance de l'industrie, il doit considérer plusieurs périodes (jours) dans son problème de génération d'enchères (BGP). Lorsque l'on considère le BGP dans un horizon glissant, une demande ouverte aux enchères sur le marché des transports peut avoir une fenêtre de service composée de plusieurs périodes consécutives (jours), et la demande peut être servie dans n'importe quelle période (jour) à l'intérieur de la fenêtre. Dans une telle situation, le transporteur doit déterminer non seulement les demandes de service (offre) mais également la période (jour) pour servir chacune des demandes afin de maximiser son profit.

Dans une enchère TSP classique à période unique, les demandes ouvertes aux enchères sont libérées avant l'enchère, et un transporteur peut avoir des demandes acquises auprès d'expéditeurs lors d'anciennes enchères ou incluses dans des contrats de service signés avec des expéditeurs auparavant. Le transporteur doit tenir compte des deux types de demandes, respectivement dénommées demandes d'interdiction et demandes réservées ci-après, dans la résolution de son BGP. De plus, lorsque l'approche de planification à horizon glissant est adoptée par un transporteur, il doit également considérer les demandes de transport susceptibles d'apparaître à l'avenir

dans son BGP lorsqu'il participe à une enchère. L'incertitude des futures demandes sur le marché du camionnage rend le BGP difficile à résoudre, car certaines informations sur les futures demandes ne peuvent pas être obtenues à l'avance. Les données historiques peuvent être utilisées pour développer des stratégies de routage qui améliorent la productivité du service (Seongmoon et al., 2005). Pour gérer l'incertitude, les transporteurs utilisent généralement les statistiques des données de demande historiques pour prédire les demandes futures. Avec une longue expérience du marché, un transporteur peut généralement estimer la probabilité d'émergence de chaque demande future. En considérant l'incertitude des demandes futures de manière probabiliste, le problème de génération d'enchères étudié dans ce chapitre peut mieux refléter la réalité du marché du transport par camions entiers.

Le BGP d'un opérateur dans une enchère TSP est traité dans ce chapitre, qui prend en compte plusieurs périodes et incertitudes. Les décisions du problème comprennent les demandes de transport à soumissionner, la période pour servir chaque demande et les itinéraires pour servir toutes les demandes, y compris les demandes réservées du transporteur.

Le BGP multi-période d'un transporteur prend en considération trois types de demandes de transport : les demandes réservées, les demandes offertes aux enchères et les demandes probabilistes. Les demandes réservées sont celles que le transporteur a acquises dans des contrats antérieurs ou passés CA. Chaque demande de ce type doit être signifiée dans un délai (jour) donné à titre d'engagement vis-à-vis de son expéditeur offrant. Les demandes offertes aux enchères sont celles ouvertes aux enchères dans CA imminente de TSP à laquelle le transporteur participera. Chaque demande d'interdiction d'enchère peut être signifiée dans n'importe quelle période de sa fenêtre temporelle composée d'une ou plusieurs périodes consécutives. Le transporteur sélectionne certaines demandes d'enchère pour former son offre (un ensemble de demandes) dans CA. Les requêtes probabilistes apparaissent avec une probabilité. Des demandes de ce type peuvent être données par des fournisseurs collaborant de longue date. Une fois que de telles demandes apparaissent, le transporteur doit les ajouter à son plan de service de transport. Les requêtes probabilistes peuvent également être utilisées pour modéliser les requêtes éventuellement acquises sur le marché du transport au comptant lors de futures enchères. Chaque demande est associée à un revenu, c'est-à-dire le revenu que le transporteur peut générer en servant la demande sans tenir compte des frais de

transport encourus. Pour chaque demande d'enchère, son revenu correspond à son prix de vente annoncé par le commissaire-priseur dans CA multi-tours décrit dans la dernière section.

Il existe deux types de décisions qui doivent être prises dans le BGP. Premièrement, le transporteur doit déterminer quelle(s) demande(s) enchérir (choisir) et dans quelles périodes chaque demande sera servie. Deuxièmement, pour chaque période, le transporteur doit déterminer les tournées (itinéraires) pour servir toutes ses demandes. Puisque chaque demande de transport par camion peut être représentée par une voie avec une origine et une destination, le problème de génération d'enchères étudié peut être formulé comme un LCP multi-période stochastique avec trois types de voies. Étant donné que des voies probabilistes peuvent apparaître dans les périodes futures et que les voies à desservir sont des variables de décision, le BGP considéré dans ce chapitre est une nouvelle variante du LCP.

Ce chapitre contribue à ce problème difficile dans les deux aspects suivants.

Premièrement, en adoptant l'approche de scénario de l'optimisation stochastique, un modèle de programmation linéaire mixte en nombres entiers (MILP) est formulé pour le problème. L'objectif du modèle est de maximiser le bénéfice net total attendu du transporteur dans un horizon de planification de plusieurs périodes. Inspiré par Ergun et al. (Ö. Ergun et al., 2007a; Ö. Ergun et al., 2007b), le modèle adopte une formulation du problème de recouvrement de voies (LCP), bien que notre problème soit un problème de maximisation. Ce modèle prend en considération trois types de demandes : les demandes d'enchères, c'est-à-dire les demandes ouvertes aux enchères, les demandes réservées qui doivent être servies par le transporteur et les demandes probabilistes dont l'émergence est incertaine. Les routes pour servir toutes les demandes sont déterminées en résolvant une nouvelle variante de LCP avec des fonctionnalités multi-périodes et probabilistes supplémentaires. La raison de l'adoption de l'approche par scénarios pour résoudre le problème approximativement est sa grande complexité en raison de sa nature stochastique. Dans cette approche, chaque scénario correspond à une réalisation possible des paramètres aléatoires (requêtes futures) du problème. Pour un nombre donné de scénarios, le modèle de programmation stochastique du problème peut être transformé en un modèle d'équivalence déterministe, qui peut être résolu de manière optimale par un algorithme exact. Selon la loi des grands nombres en théorie des probabilités, lorsque le nombre de scénarios est pris suffisamment grand, la solution du modèle d'équivalence

déterministe peut bien approcher la solution du problème d'optimisation stochastique.

Deuxièmement, une approche de décomposition de Benders (BD) est proposée pour résoudre le modèle MILP. Dans l'approche, le problème d'origine (modèle) est divisé en plusieurs sous-problèmes, un pour chaque scénario. Sur la base des solutions des sous-problèmes, un problème maître restreint est résolu avec des contraintes supplémentaires (coupes de pliage) ajoutées à chaque itération du BD. Pour accélérer ce processus itératif, une technique de génération de coupes Pareto-optimales (Magnanti & Wong, 1981) est appliquée dans la BD. Les performances de l'approche proposée sont évaluées par des expériences numériques sur plusieurs ensembles d'instances générées aléatoirement. Une comparaison avec le solveur CPLEX sur les instances démontre que l'approche BD est beaucoup plus efficace que le solveur CPLEX pour résoudre de grandes instances. De plus, l'intérêt de considérer les requêtes probabilistes et multi-périodes dans le BGP de CA est également évalué.

## **A.6 Conclusions et perspectives**

Le transport par camions entiers est une partie importante de l'industrie du transport, dans laquelle les expéditeurs se procurent des services de transport auprès des transporteurs. L'achat de services de transport est souvent réalisé par enchères combinatoires. La conception du mécanisme d'enchères combinatoires, ainsi que la méthode pour résoudre l'un des principaux problèmes de décision, le problème de génération d'enchères, affectent l'efficacité de l'enchère combinatoire. En concevant des mécanismes d'enchères efficaces et des méthodes efficaces pour résoudre les problèmes de génération d'enchères, les expéditeurs et les transporteurs peuvent respectivement réduire leurs coûts et augmenter leurs bénéfices. Cette thèse étudie trois problèmes posés dans l'achat de services de transport par camions entiers réalisés par enchères combinatoires.

Dans le premier problème, une enchère combinatoire pour l'achat de services de transport par camions entiers est étudiée, impliquant plusieurs expéditeurs et transporteurs afin de maximiser l'efficacité sociale. Ce problème est équivalent à celui qui minimise le coût total de la desserte de toutes les voies devant être externalisées par les expéditeurs. Une approche centralisée et une approche décentralisée pour résoudre ce problème sont proposées. Pour l'approche centralisée, un modèle de programmation linéaire en nombres mixtes (MILP) est formulé pour le problème et résolu par le solveur CPLEX. Pour l'approche décentralisée, deux mécanismes

d'enchères combinatoires en deux phases sont conçus, l'un avec des paquets des demandes supplémentaires d'appels d'enchères générés par le commissaire-priseur et un autre avec des enchères supplémentaires générées directement par les transporteurs dans la deuxième phase. Les deux phases sont respectivement la phase d'enchère au cadran et la phase d'enchère supplémentaire. Les mécanismes d'enchères combinatoires en deux phases sont également réalisés par des codes. Les résultats des calculs montrent que par rapport à la vente aux seulement enchère au cadran, les mécanismes à deux phases conçus présentent des avantages évidents en termes d'efficacité du temps et d'économies pour le commissaire-priseur. Parallèlement, l'efficacité sociale du résultat de l'enchère (allocation des demandes) est améliorée par les deux mécanismes.

Dans le deuxième problème, un problème de génération d'enchères d'un transporteur dans une enchère combinatoire pour l'achat de services de transport par camions entiers est étudié afin de maximiser le profit net du transporteur. Dans ce problème, à la fois les engagements et les contrats préexistants (voies réservées) et les nouvelles demandes qui doivent être sélectionnées dans l'enchère (voies offerte aux enchère) sont pris en compte. Le transporteur doit décider à la fois pour quelles voies faire une offre dans le cadre de l'enchère combinatoire et de l'itinéraire pour desservir à la fois les voies réservées et les voies offerte aux enchère pour l'enchère. Un modèle de programmation linéaire inter mixte et un modèle de partition d'ensemble sont formulés pour le problème. Un algorithme de génération de colonnes est également proposé pour le problème avec le sous-problème (problème élémentaire du plus court chemin) résolu par programmation dynamique avec algorithme d'étiquetage et algorithme de recherche locale. Des expériences numériques sont menées pour comparer les solutions obtenues par le modèle MILP résolu par le solveur CPLEX et l'algorithme de génération de colonnes. Les résultats démontrent que l'algorithme proposé peut rapidement trouver une solution quasi optimale du problème étudié.

Dans le troisième problème, le problème de génération d'enchères pour un seul transporteur en enchères combinatoire pour l'achat en services de transport par camions entiers est étendu à celui qui prend en compte à la fois les périodes multiples et l'incertitude dans l'achat des services de transport par camions entiers. Ce problème d'optimisation stochastique est formulé comme un modèle de programmation linéaire en nombres entiers mixtes via l'optimisation de scénarios et l'équivalence déterministe. Pour résoudre ce modèle, une approche de décomposition de Benders est proposée

avec une coupe Pareto-optimale pour accélérer le processus de l'approche. Les résultats informatiques démontrent que l'approche de décomposition de Benders proposée est beaucoup plus efficace que le solveur CPLEX en termes de temps de calcul pour résoudre de grandes instances du modèle. La valeur de la prise en compte des demandes incertaines et des périodes multiples dans la génération d'enchères est également évaluée par des expériences numériques. Les résultats montrent que considérer à l'avance les demandes incertaines peut améliorer le bénéfice net du transporteur et considérer plusieurs périodes peut améliorer la compétitivité du transporteur.

Bien que des mécanismes et des algorithmes efficaces soient proposés pour résoudre les problèmes soulevés par les enchères combinatoires pour l'achat en services de transport par camions entiers, de nombreux travaux peuvent encore être effectués pour améliorer les solutions aux problèmes et étendre le problème à un environnement plus complexe et applicable.

Premièrement, pour les mécanismes des enchères combinatoires, les méthodes de la phase d'enchères supplémentaires proposées dans cette thèse peuvent ne pas être le seul moyen de générer des enchères supplémentaires, et la phase d'enchères supplémentaires peut ne pas être la seule approche pour accélérer le processus de l'enchère pour trouver une allocation efficace des voies offerte aux enchères. La question de savoir s'il existe de meilleures méthodes et approches peut être un problème intéressant à explorer à l'avenir. Deuxièmement, pour le problème de génération d'enchère par camions entiers étudié au chapitre 4, les travaux futurs peuvent se concentrer sur l'amélioration des approches actuelles pour obtenir la solution initiale du problème maître restreint et les algorithmes pour résoudre le sous-problème dans l'algorithme de génération de colonnes. Trouver de nouvelles approches efficaces pour résoudre le sous-problème est également significatif. Troisièmement, pour le problème de génération d'enchère compte tenu des périodes multiples et de l'incertitude, trouver d'autres moyens d'accélérer la décomposition de Benders est significatif. Pendant ce temps, il peut également être important de trouver un algorithme heuristique efficace pour résoudre le problème à grande échelle.



## References

- Abrache, J., Crainic, T.G. & Gendreau, M. (2004). Design issues for combinatorial auctions. *Quarterly Journal of the Belgian, French and Italian Operations Research Societies*, 2(1), 1-33.
- Abrache, J., Crainic, T.G., Gendreau, M. & Rekik, M. (2007). Combinatorial auctions. *Annals of Operations Research*, 153(1), 131-164.
- An, N., Elmaghraby, W. & Keskinocak, P. (2005). Bidding strategies and their impact on revenues in combinatorial auctions. *Journal of Revenue and Pricing Management*, 3(4), 337-357.
- Archetti, C., Feillet, D., Hertz, A. & Speranza, M.G. (2009). The capacitated team orienteering and profitable tour problems. *Journal of the Operational Research Society*, 60(6), 831-842.
- Archetti, C., Speranza, M.G., Corberán, Á., Sanchis, J.M. & Plana, I. (2013). The Team Orienteering Arc Routing Problem. *Transportation Science*, 48(3), 442-457.
- Arroyo, J.M. & Conejo, A.J. (2002). Multiperiod auction for a pool-based electricity market. *IEEE Transactions on Power Systems*, 17(4), 1225-1231.
- Arunapuram, S., Mathur, K. & Solow, D. (2003). Vehicle Routing and Scheduling with Full Truckloads. *Transportation Science*, 37(2), 170-182.
- ATA. (2019). American Trucking Association. <https://www.trucking.org/economics-and-industry-data>, Accessed May 27, 2021.
- Ausubel, L., Cramton, P. & Milgrom, P. (2006). The clock-proxy auction: a practical combinatorial auction design. In: P. Cramton, Y. Shoham & R. Steinberg, *Combinatorial Auctions* (Chapter 5). Boston: MIT press.
- Ausubel, L. & Milgrom, P. (2006). The Lovely but Lonely Vickrey Auction. In: P. Cramton, Y. Shoham & R. Steinberg, *Combinatorial Auctions* (Chapter 1). Boston: MIT press.
- Ausubel, L.M. & Baranov, O. (2017a). A Practical Guide to the Combinatorial Clock Auction. In: J.K. Goeree & M. Bichler, *Handbook of Spectrum Auction Design* (pp. 170-186). Cambridge: Cambridge University Press.
- Ausubel, L.M. & Baranov, O. (2017b). A Practical Guide to the Combinatorial Clock Auction. *The Economic Journal*, 127(605), F334-F350.
- Ball, M.O., Golden, B.L., Assad, A.A. & Bodin, L.D. (1983). Planning for Truck Fleet Size in the Presence of a Common-carrier Option. *Decision Sciences*, 14(1), 103-120.
- Berger, S. & Bierwirth, C. (2010). Solutions to the request reassignment problem in collaborative carrier networks. *Transportation Research Part E: Logistics and Transportation Review*, 46(5), 627-638.
- Berhault, M., Huang, H., Keskinocak, P., Koenig, S., Elmaghraby, W., Griffin, P. & Kleywegt, A. (2003). Robot exploration with combinatorial auctions. In: *Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and*

- Systems (IROS 2003) (Cat. No.03CH37453) (Vol. 2, pp. 1957-1962 vol.1952).
- Bichler, M., Pikhovskiy, A. & Setzer, T. (2009). An Analysis of Design Problems in Combinatorial Procurement Auctions. *Business & Information Systems Engineering*, 1(1), 111-117.
- Bouyahyious, K.E. & Bellabdaoui, A. (2017). An ant colony optimization algorithm for solving the full truckload vehicle routing problem with profit. In: 2017 International Colloquium on Logistics and Supply Chain Management (LOGISTIQUA) (pp. 142-147).
- Brunekreeft, G. (2001). A multiple-unit, multiple-period auction in the British electricity spot market. *Energy Economics*, 23(1), 99-118.
- Budde, D.-K.M. (2014). Procurement Auctions in Logistics and Transportation (PhD Thesis). Technical University of Munich.
- Buer, T. (2014). An exact and two heuristic strategies for truthful bidding in combinatorial transport auctions. ArXiv, abs/1406.1928.
- Caplice, C. (2007). Electronic Markets for Truckload Transportation. *Production and Operations Management*, 16(4), 423-436.
- Caplice, C. & Sheffi, Y. (2003). Optimization-based Procurement for Transportation Services. *Journal of Business Logistics*, 24(2), 109-128.
- Caplice, C. & Sheffi, Y. (2006). Combinatorial Auctions for Truckload Transportation. In: P. Cramton, Y. Shoham & R. Steinberg, *Combinatorial Auctions*. Boston: MIT Press.
- Chang, T.-S. (2009). Decision support for truckload carriers in one-shot combinatorial auctions. *Transportation Research Part B: Methodological*, 43(5), 522-541.
- Chao, I.M., Golden, B.L. & Wasil, E.A. (1996). The team orienteering problem. *European Journal of Operational Research*, 88(3), 464-474.
- Chen, H. (2016). Combinatorial clock-proxy exchange for carrier collaboration in less than truck load transportation. *Transportation Research Part E: Logistics and Transportation Review*, 91, 152-172.
- Chen, R.L.-Y., AhmadBeygi, S., Cohn, A., Beil, D.R. & Sinha, A. (2009). Solving Truckload Procurement Auctions Over an Exponential Number of Bundles. *Transportation Science*, 43(4), 493-510.
- Collignon, S.E. (2016). Exploratory and Empirical Analysis of E-Marketplaces for Truck Transportation Services Procurement. Blacksburg, VA.
- Cramton, P., Shoham, Y. & Steinberg, R. (2006). *Combinatorial Auctions*. Boston: MIT press.
- Dai, B. & Chen, H. (2011). A multi-agent and auction-based framework and approach for carrier collaboration. *Logistics Research*, 3(2-3), 101-120.
- Dantzig, G.B. & Wolfe, P. (1960). Decomposition Principle for Linear Programs. *Operations Research*, 8(1), 101-111.
- Day, R.W. & Raghavan, S. (2008). A combinatorial procurement auction featuring bundle price revelation without free-riding. *Decision Support Systems*, 44(3), 621-640.

- De Vries, S. & Vohra, R.V. (2003). Combinatorial Auctions: A Survey. *INFORMS Journal on Computing*, 15(3), 284-309.
- Desrosiers, J., Laporte, G., Sauve, M., Soumis, F. & Taillefer, S. (1988). Vehicle routing with full loads. *Computers & Operations Research*, 15(3), 219-226.
- El-Hajj, R., Moukrim, A., Chebaro, B. & Kobeissi, M. (2015). A column generation algorithm for the team orienteering problem with time windows. In: *The 45th International Conference on Computers & Industrial Engineering (CIE45)*. Metz, France.
- Elmaghraby, W. & Keskinocak, P. (2000). Technology for transportation bidding at The Home Depot. Teaching Case, Georgia Institute of Technology.
- Elmaghraby, W. & Keskinocak, P. (2004). Combinatorial Auctions in Procurement. In: *The Practice of Supply Chain Management: Where Theory and Application Converge* (pp. 245-258). Boston, MA: Springer US.
- Epstein, R., Henríquez, L., Catalán, J., Weintraub, G.Y., Martínez, C. & Espejo, F. (2004). A combinatorial auction improves school meals in Chile: a case of OR in developing countries. *International Transactions in Operational Research*, 11(6), 593-612.
- Ergun, O., Kuyzu, G. & Savelsbergh, M. (2003). The Lane Covering Problem. Manuscript.
- Ergun, Ö., Kuyzu, G. & Savelsbergh, M. (2007a). Reducing Truckload Transportation Costs Through Collaboration. *Transportation Science*, 41(2), 206-221.
- Ergun, Ö., Kuyzu, G. & Savelsbergh, M. (2007b). Shipper collaboration. *Computers & Operations Research*, 34(6), 1551-1560.
- eurostat. (2018). European Statistical Office. [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Freight\\_transport\\_statistics](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Freight_transport_statistics), Accessed September 30, 2020.
- Faiz, T.I., Vogiatzis, C. & Noor-E-Alam, M. (2019). A column generation algorithm for vehicle scheduling and routing problems. *Computers & Industrial Engineering*, 130, 222-236.
- Feillet, D., Dejax, P., Gendreau, M. & Gueguen, C. (2004). An exact algorithm for the elementary shortest path problem with resource constraints: Application to some vehicle routing problems. *Networks*, 44(3), 216-229.
- Figliozzi, M., Mahmassani, H. & Jaillet, P. (2004a). Auction settings and performance of electronic marketplaces for truckload transportation services. *Transport. Res. Rec.*, 1906.
- Figliozzi, M., Mahmassani, H. & Jaillet, P. (2004b). Competitive Performance Assessment of Dynamic Vehicle Routing Technologies Using Sequential Auctions. *Transportation Research Record Journal of the Transportation Research Board*, 1882, 10-18.
- Figliozzi, M., Mahmassani, H. & Jaillet, P. (2005). Impacts of Auction Settings on the Performance of Truckload Transportation Marketplaces. *Transportation Research Record Journal of the Transportation Research Board*, 1906, 89-96.

- Figliozzi, M., Mahmassani, H. & Jaillet, P. (2006). Quantifying Opportunity Costs in Sequential Transportation Auctions for Truckload Acquisition. *Transportation Research Record Journal of the Transportation Research Board*, 1964, 247-252.
- Gansterer, M. & Hartl, R.F. (2018). Centralized bundle generation in auction-based collaborative transportation. *OR Spectrum*, 40(3), 613-635.
- Garrido, R.A. (2007). Procurement of transportation services in spot markets under a double-auction scheme with elastic demand. *Transportation Research Part B: Methodological*, 41(9), 1067-1078.
- Geoffrion, A.M. (1972). Generalized Benders Decomposition. *JOURNAL OF OPTIMIZATION THEORY AND APPLICATIONS*, 10(4).
- Geweke, J.F. & Singleton, K.J. (1980). Interpreting the Likelihood Ratio Statistic in Factor Models When Sample Size is Small. *Journal of the American Statistical Association*, 75(369), 133-137.
- Ghiani, G., Manni, E. & Triki, C. (2008). The lane covering problem with time windows. *Journal of Discrete Mathematical Sciences and Cryptography*, 11(1), 67-81.
- Gronalt, M., Hartl, R.F. & Reimann, M. (2003). New savings based algorithms for time constrained pickup and delivery of full truckloads. *European Journal of Operational Research*, 151(3), 520-535.
- Gschwind, T., Irnich, S., Rothenbächer, A.-K. & Tilk, C. (2018). Bidirectional labeling in column-generation algorithms for pickup-and-delivery problems. *European Journal of Operational Research*, 266(2), 521-530.
- Hammami, F., Rekik, M. & Coelho, L. (2020). The Combinatorial Bid Construction Problem with Stochastic Prices for Transportation Services Procurement.
- Hammami, F., Rekik, M. & Coelho, L.C. (2021). Exact and hybrid heuristic methods to solve the combinatorial bid construction problem with stochastic prices in truckload transportation services procurement auctions. *Transportation Research Part B: Methodological*, 149, 204-229.
- <http://comopt.ifi.uni-heidelberg.de/software/TSPLIB95/tsp/>. Discrete and Combinatorial Optimization: Software and Data, Accessed December 19, 2020.
- Huang, G.Q. & Xu, S.X. (2013). Truthful multi-unit transportation procurement auctions for logistics e-marketplaces. *Transportation Research Part B: Methodological*, 47, 127-148.
- Irnich, S. & Desaulniers, G. (2005). Shortest Path Problems with Resource Constraints. In: G. Desaulniers, J. Desrosiers & M.M. Solomon, *Column Generation* (pp. 33-65). Boston, MA: Springer US.
- Janssen, M. & Kasberger, B. (2019). On the clock of the combinatorial clock auction. *Theoretical Economics*, 14(4), 1271-1307.
- Jothi Basu, R., Subramanian, N. & Cheikhrouhou, N. (2015). Review of Full Truckload Transportation Service Procurement. *Transport Reviews*, 35(5), 599-621.
- Kelly, F. & Steinberg, R. (2000). A Combinatorial Auction with Multiple Winners for Universal Service. *Management Science*, 46(4), 586-596.

- Keshtkaran, M., Ziarati, K., Bettinelli, A. & Vigo, D. (2016). Enhanced exact solution methods for the Team Orienteering Problem. *International Journal of Production Research*, 54(2), 591-601.
- Kutanoglu, E. & Wu, S.D. (1999). On combinatorial auction and Lagrangean relaxation for distributed resource scheduling. *IIE Transactions*, 31(9), 813-826.
- Kuyzu, G. (2017). Lane covering with partner bounds in collaborative truckload transportation procurement. *Computers & Operations Research*, 77, 32-43.
- Kuyzu, G., Akyol, Ç.G., Ergun, Ö. & Savelsbergh, M. (2015). Bid price optimization for truckload carriers in simultaneous transportation procurement auctions. *Transportation Research Part B: Methodological*, 73, 34-58.
- Kwon, R., Lee, C. & Ma, Z. (2005). An integrated combinatorial auction mechanism for truckload transportation procurement.
- Lafkihi, M., Pan, S. & Ballot, E. (2017). Mechanisms for Freight Transportation Service Procurement: a Literature-based Analysis. In: *The 47th International Conference on Computers & Industrial Engineering (CIE47)*. Lisbon, Portugal.
- Lafkihi, M., Pan, S. & Ballot, E. (2019). Freight transportation service procurement: A literature review and future research opportunities in omnichannel E-commerce. *Transportation Research Part E: Logistics and Transportation Review*, 125, 348-365.
- Land, A., Powell, S. & Steinberg, R. (2006). PAUSE: A Computationally Tractable Combinatorial Auction. In: P. Cramton, Y. Shoham & R. Steinberg, *Combinatorial Auctions* (Chapter 6). Boston: MIT press.
- Lau, H.C., Cheng, S.F., Leong, T.Y., Park, J.H. & Zhao, Z. (2007). Multi-Period Combinatorial Auction Mechanism for Distributed Resource Allocation and Scheduling. In: *2007 IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT'07)* (pp. 407-411).
- Ledyard, J.O., Olson, M., Porter, D., Swanson, J.A. & Torma, D.P. (2002). The First Use of a Combined-Value Auction for Transportation Services. *INFORMS Journal on Applied Analytics*, 32(5), 4-12.
- Lee, C.-G., Kwon, R.H. & Ma, Z. (2007). A carrier's optimal bid generation problem in combinatorial auctions for transportation procurement. *Transportation Research Part E: Logistics and Transportation Review*, 43(2), 173-191.
- Levin, J. & Skrzypacz, A. (2016). Properties of the Combinatorial Clock Auction. *American Economic Review*, 106(9), 2528-2551.
- Leyton-Brown, K., Shoham, Y. & Tennenholtz, M. (2000). An algorithm for multi-unit combinatorial auctions. In: *Seventeenth National Conference on Artificial Intelligence and Twelfth Conference on Innovative Applications of Artificial Intelligence* (pp. 56-61).
- Li, J. & Lu, W. (2014). Full truckload vehicle routing problem with profits. *Journal of Traffic and Transportation Engineering (English Edition)*, 1(2), 146-152.
- Li, J., Rong, G. & Feng, Y. (2015). Request selection and exchange approach for carrier collaboration based on auction of a single request. *Transportation Research Part E:*

- Logistics and Transportation Review, 84, 23-39.
- Lim, A., Rodrigues, B. & Xu, Z. (2008). Transportation Procurement with Seasonally Varying Shipper Demand and Volume Guarantees. *Operations Research*, 56(3), 758-771.
- Lunander, A. & Lundberg, S. (2013). Bids and Costs in Combinatorial and Noncombinatorial Procurement auctions—Evidence from Procurement of Public Cleaning Contracts. *Contemporary Economic Policy*, 31(4), 733-745.
- Lyu, K., Chen, H. & Che, A. (2020). Combinatorial Auction for Truckload Transportation Service Procurement with Auctioneer-Generated Supplementary Bundles of Requests. In: 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC) (pp. 1-6).
- Lyu, K., Chen, H. & Che, A. (2021). A Bid Generation Problem in Truckload Transportation Service Procurement Considering Multiple Periods and Uncertainty: Model and Benders Decomposition Approach. *IEEE Transactions on Intelligent Transportation Systems*, DOI: 10.1109/TITS.2021.3091692, 1-14.
- Ma, Z. (2008). Combinatorial Auctions for Truckload Transportation Procurement (PhD Thesis). Mechanical & Industrial Engineering University of Toronto.
- Magnanti, T.L. & Wong, R.T. (1981). Accelerating Benders Decomposition: Algorithmic Enhancement and Model Selection Criteria. *Operations Research*, 29(3), 464-484.
- Mamaghani, E., Chen, H. & Prins, C. (2019a). A Hybrid Genetic and Simulation Annealing Approach for a Multi-period Bid Generation Problem in Carrier Collaboration. In: ICORES 8th International Conference on Operations Research and Enterprise Systems. Prague-Czech Republic.
- Mamaghani, E., Chen, H., Prins, C. & Demir, E. (2019b). An Improved Tabu Search Algorithm for a Multi-Period Bid Generation Problem with the Consideration of Delivery Lead Time. *IFAC-PapersOnLine*, 52(13), 2602-2607.
- Mes, M.R.K. (2008). Sequential auctions for full truckload allocation (PhD Thesis). Enschede, University of Twente.
- MOT. (2019). Ministry of Transport of the People's Republic of China. <https://www.mot.gov.cn/tongjishuju/gonglu/index.html>, Accessed January 20, 2020.
- Nandiraju, S. & Regan, A. (2003). Freight Transportation Electronic Marketplaces: A Survey of the Industry and Exploration of Important Research Issues. In: <https://escholarship.org/uc/item/9fj2c4jw>.
- Nisan, N. (2000). Bidding and Allocation in Combinatorial Auctions. In: 2nd ACM conference on Electronic commerce (pp. 1-12).
- Orlin, J.B. (1993). A Faster Strongly Polynomial Minimum Cost Flow Algorithm. *Operations Research*, 41(2), 338-350.
- Özener, O.Ö., Ergun, Ö. & Savelsbergh, M. (2011). Lane-Exchange Mechanisms for Truckload Carrier Collaboration. *Transportation Science*, 45(1), 1-17.
- Park, S. & Rothkopf, M.H. (2005). Auctions with bidder-determined allowable

- combinations. *European Journal of Operational Research*, 161(2), 399-415.
- Pekeč, A. & Rothkopf, M.H. (2003). Combinatorial Auction Design. *Management Science*, 49(11), 1485-1503.
- Poggi, M., Viana, H. & Uchoa, E. (2010). The Team Orienteering Problem: Formulations and Branch-Cut and Price (Vol. 14).
- Rassenti, S.J., Smith, V.L. & Bulfin, R.L. (1982). A Combinatorial Auction Mechanism for Airport Time Slot Allocation. *The Bell Journal of Economics*, 13(2), 402-417.
- Riera-Ledesma, J. & Salazar-González, J.J. (2017). Solving the Team Orienteering Arc Routing Problem with a column generation approach. *European Journal of Operational Research*, 262(1), 14-27.
- Ropke, S. & Cordeau, J.-F. (2009). Branch and Cut and Price for the Pickup and Delivery Problem with Time Windows. *Transportation Science*, 43, 267-286.
- Rothkopf, M.H., Pekeč, A. & Harstad, R.M. (1998). Computationally Manageable Combinatorial Auctions. *Management Science*, 44(8), 1131-1147.
- Schwind, M., Gujo, O. & Vykoukal, J. (2009). A combinatorial intra-enterprise exchange for logistics services. *Information Systems and e-Business Management*, 7(4), 447-471.
- Seongmoon, K., Lewis, M.E. & White, C.C. (2005). Optimal vehicle routing with real-time traffic information. *IEEE Transactions on Intelligent Transportation Systems*, 6(2), 178-188.
- Sheffi, Y. (2004). Combinatorial Auctions in the Procurement of Transportation Services. *INFORMS Journal on Applied Analytics*, 34(4), 245-252.
- Song, J. & Regan, A. (2003). Combinatorial Auctions for Transportation Service Procurement: The Carrier Perspective. *Transportation Research Record*, 1833(1), 40-46.
- Song, J. & Regan, A. (2005). Approximation algorithms for the bid construction problem in combinatorial auctions for the procurement of freight transportation contracts. *Transportation Research Part B: Methodological*, 39(10), 914-933.
- Srivastava, N.K., Viswanadham, N. & Kameshwaran, S. (2008). Procurement of global logistics services using combinatorial auctions. In: 2008 IEEE International Conference on Automation Science and Engineering (pp. 297-302).
- Tian, T., Wang, N., Ma, H. & Lim, A. (2011). A transportation service procurement problem with combinatorial auction. In: ICSSSM11 (pp. 1-6).
- Triki, C., Oprea, S., Beraldi, P. & Crainic, T.G. (2014). The stochastic bid generation problem in combinatorial transportation auctions. *European Journal of Operational Research*, 236(3), 991-999.
- Vitale, I. & Dondo, R. (2020). A Dynamic-Pricing Label-Setting Algorithm for Solving the Elementary Resource Constrained Shortest Path Problem.
- Wang, C., Handoko, S.D. & Lau, H.C. (2014). An auction with rolling horizon for urban consolidation centre. In: 2014 IEEE International Conference on Service Operations and Logistics, and Informatics (pp. 438-443).
- Wang, D. & Wang, N. (2015). Quantum computation based bundling optimization for

- combinatorial auction in freight service procurements. *Computers & Industrial Engineering*, 89, 186-193.
- Wang, X. & Kopfer, H. (2013). Dynamic Collaborative Transportation Planning: A Rolling Horizon Planning Approach. In: D. Pacino, S. Voß & R.M. Jensen, *Computational Logistics. ICCL 2013. Lecture Notes in Computer Science (Vol. 8197)*. Berlin, Heidelberg: Springer.
- Wang, X. & Kopfer, H. (2015). Rolling horizon planning for a dynamic collaborative routing problem with full-truckload pickup and delivery requests. *Flexible Services and Manufacturing Journal*, 27(4), 509-533.
- Wang, X. & Xia, M. (2005). Combinatorial Auctions for Transportation Service Procurement. *Transportation Research Record*, 1923(1), 189-198.
- Xu, S.X. & Huang, G.Q. (2013). Transportation service procurement in periodic sealed double auctions with stochastic demand and supply. *Transportation Research Part B: Methodological*, 56, 136-160.
- Xu, S.X., Huang, G.Q. & Cheng, M. (2017). Truthful, Budget-Balanced Bundle Double Auctions for Carrier Collaboration. *Transportation Science*, 51(4), 1365-1386.
- Xue, N., Bai, R., Qu, R. & Aickelin, U. (2021). A hybrid pricing and cutting approach for the multi-shift full truckload vehicle routing problem. *European Journal of Operational Research*, 292(2), 500-514.
- Yan, F., Ma, Y., Xu, M. & Ge, X. (2018). Transportation Service Procurement Bid Construction Problem from Less Than Truckload Perspective. *Mathematical Problems in Engineering*, 2018, 1728512.
- You, F., Wassick, J.M. & Grossmann, I.E. (2009). Risk management for a global supply chain planning under uncertainty: Models and algorithms. *AIChE Journal*, 55(4), 931-946.
- Zhou, C., Liu, Y., Tan, Y. & Liao, L. (2006a). Real-time Operational Strategies for Truckload Pickup and Delivery Problems. In: 2006 5th IEEE International Conference on Cognitive Informatics (Vol. 2, pp. 897-902).
- Zhou, C., Tan, Y., Liao, L. & Liu, Y. (2006b). Real-time Truckload Fleet Assignment and Scheduling Problem. In: Sixth International Conference on Intelligent Systems Design and Applications (Vol. 3, pp. 138-143).
- Zhou, C.F. (2013). Dynamic Truckload Pick-Up and Delivery Problem with Time Windows. *Advanced Materials Research*, 694-697, 3558-3561.
- Zhou, L. & Xu, H. (2017). An Efficient Double Auction Mechanism for On-Demand Transport Services in Cloud-Based Mobile Commerce. In: 2017 5th IEEE International Conference on Mobile Cloud Computing, Services, and Engineering (MobileCloud) (pp. 25-30).



# Ke LYU

## Doctorat : Optimisation et Sûreté des Systèmes

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### Études sur le mécanisme d'enchères et la génération d'enchères dans l'achat de services de transport

Le transport par camions entiers est un mode courant de transport de marchandises, qui représente une part importante de l'industrie de transport, où les expéditeurs achètent des services de transport auprès des transporteurs. L'achat de services de transport est souvent réalisé par des enchères. Par concevoir des mécanismes d'enchères efficaces et des méthodes efficaces pour résoudre les problèmes de génération d'enchères associés, les expéditeurs et les transporteurs peuvent réduire leurs coûts et augmenter leurs bénéfices respectivement.

Cette thèse étudie trois problèmes soulevés dans l'achat de services de transport par camions entiers réalisé par une enchère combinatoire. Premièrement, deux mécanismes d'enchères combinatoires à deux phases sont conçus avec des paquets supplémentaires de demandes offerts à l'enchère générés respectivement par le commissaire-priseur et les transporteurs dans la deuxième phase. Deuxièmement, un algorithme de génération de colonnes est proposé pour résoudre le problème de génération d'enchères apparu dans l'enchère combinatoire. Enfin, le problème de génération d'enchères est étendu à un problème qui tient compte à la fois plusieurs périodes et l'incertitude dans l'achat de services de transport par camions entières. Ce problème d'optimisation stochastique est formulé par l'optimisation de scénario et l'équivalence déterministe. Pour résoudre ce modèle, une approche de décomposition de Benders est proposée.

**Mots clés :** transport de marchandises – vente aux enchères – problème de tournées de véhicules – optimisation combinatoire – programmation (mathématiques).

### Studies on Auction Mechanism and Bid Generation in the Procurement of Truckload Transportation Services

Truckload transportation is a common mode of freight transportation, which accounts for a substantial portion of transportation industry, where shippers procure transportation services from carriers. Transportation service procurement is often realized by auction. Through designing effective auction mechanisms and efficient methods for solving related bid generation problems, shippers and carriers can save costs and increase profits respectively.

This thesis studies three problems raised in the procurement of truckload transportation services realized by combinatorial auctions. Firstly, two two-phase combinatorial auction mechanisms are designed with supplementary bundles of requests offered for bid generated by the auctioneer and the carriers respectively in the second phase. Secondly, a column generation algorithm is proposed to solve the bid generation problem appeared in the combinatorial auction. Finally, the bid generation problem is extended to one that considers both multiple periods and uncertainty in truckload transportation service procurement. This stochastic optimization problem is formulated through scenario optimization and deterministic equivalence. To solve this model, a Benders decomposition approach is proposed.

**Keywords:** freight and freightage – auctions – vehicle routing problem – combinatorial optimization – programming (mathematics).

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