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Models and methods for decentralized decision in logistics networks

Yaheng Cui

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THÈSE

présentée en vue
d'obtenir le grade de

DOCTEUR

en

Spécialité : Informatique

par

Yaheng CUI

DOCTORAT DELIVRE PAR CENTRALE LILLE

Titre de la thèse :

**Modèles et méthodes de décision décentralisée dans les réseaux
logistiques**

**Models and methods for decentralized decision in logistics
networks**

Soutenue le 18/12/2020 devant le jury d'examen :

Président	Ms. Dominique Quadri	Professeur, Université Paris Sud - Paris Saclay
Rapporteur	M. Nicolas Józefowicz	Professeur, Université de Lorraine
Rapporteur	M. Patrick Charpentier	Professeur, Université de Lorraine
Examineur	Ms. Dominique Quadri	Professeur, Université Paris Sud - Paris Saclay
Examineur	M. Damien Trentesaux	Professeur, Université Polytechnique Hauts-de-France
Directeur de thèse	Ms. Luce Brotocorne	Professeur, Inria Lille-Nord Europe
Co-directeur de thèse	M. Eric Ballot	Professeur, Mines ParisTech

Thèse préparée dans le Laboratoire CRISAL
au sein d'équipe INOCS à l'Inria Lille-Nord Europe
École Doctorale SPI 072

*À mes parents,
à toute ma famille,
à mes professeurs,
et à mes chère(s) ami(e)s.*

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Chapter 1

General Introduction

1.1 Research context

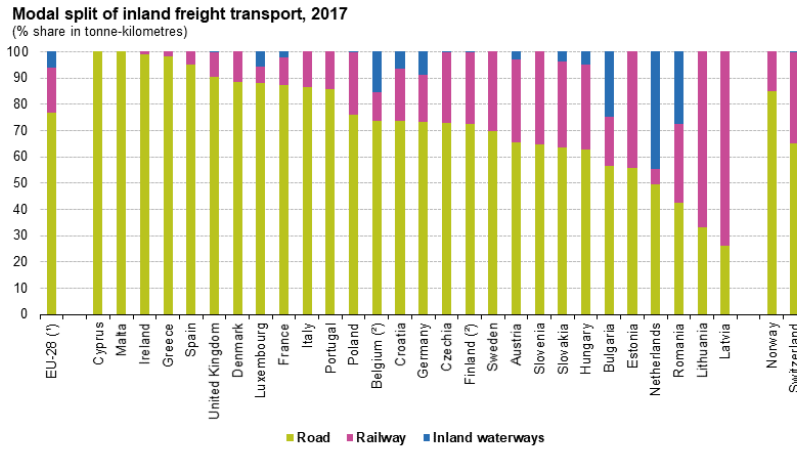
Nowadays, freight transportation is a vital component for the economy and the supply chain. In Europe, freight transport contributes around 5% to the total gross domestic product (GDP). Among all transportation mode, road freight transport shares almost 80% of the inland transportation activities due to the associated flexibility and capability to provide efficient and rapid door-to-door services in most countries, see Figure 1.1. The total operating revenue (see Figure 1.3) and the total revenue (see Figure 1.4) are increasing because of the globalized trade and economic growth. As in France, the contribution to GDP of transport is 14% i.e. 321 billions of euros, and 5.4% GDP is coming from the road freight transportation (INSEE, 2018*).

Notice that, in US, full truckload transportation shares almost 70% of the freight transport market (see Figure 1.2). Therefore, throughout this thesis, we mainly focus on the study of full truckload transportation to highlight its importance.

However, the carriers in freight transport market are facing several challenges to keep and enlarge their market share and thus improve their revenue. One of the challenges comes from the increasing intense competition at three levels: among the countries and regions, among the various transportation modes, and among the abundant carriers and logistics services providers. In this strong competitive environments, both shippers and carriers are under pressure to reduce their costs

*<https://www.unionroutiere.fr/publication/consultez-faits-chiffres-2018/>

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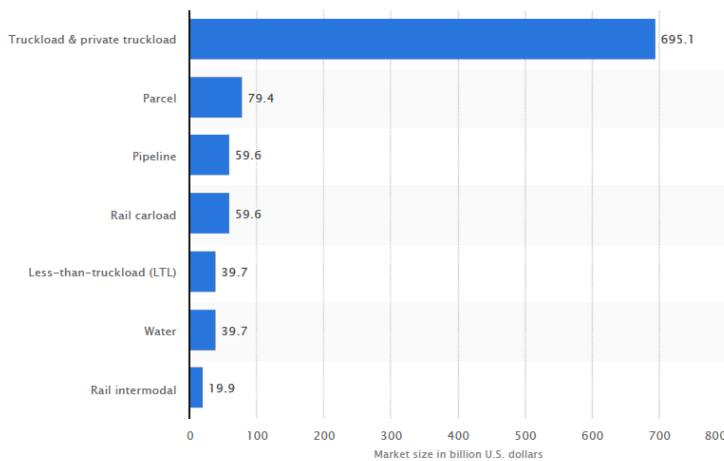


Note: Figures may not add up to 100% due to rounding.
 (*) EU-28 includes rail transport estimates for Belgium, road freight transport for Malta and inland waterways transport for Finland.
 (†) Estimates.
 (‡) Estimates.
 Source: Eurostat (online data code: tran_hv_fmmod)



Figure 1.1: Modal split of inland freight transport, 2017

Market size of the U.S. freight transportation in 2018, by segment
(in billion U.S. dollars)



Details: United States; American Trucking Associations; Stifel; 2018

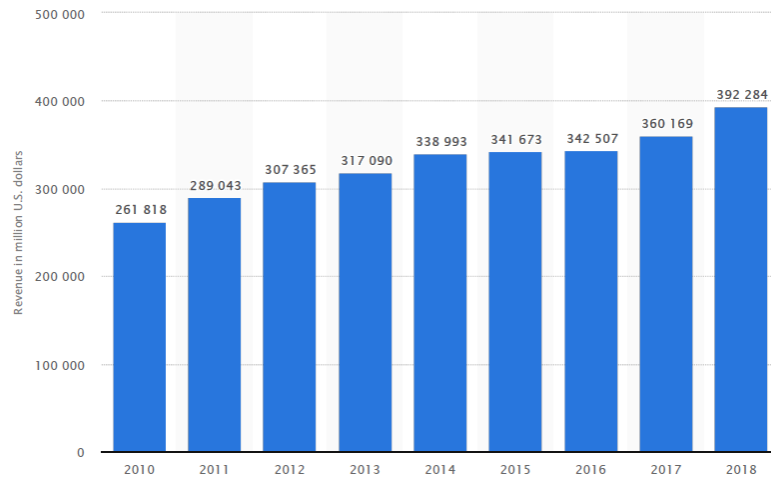
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Figure 1.2: Market size of the U.S. freight transportation in 2018

1.1 Research context

Total operating revenues of the U.S. trucking industry from 2010 to 2018

(in million U.S. dollars)



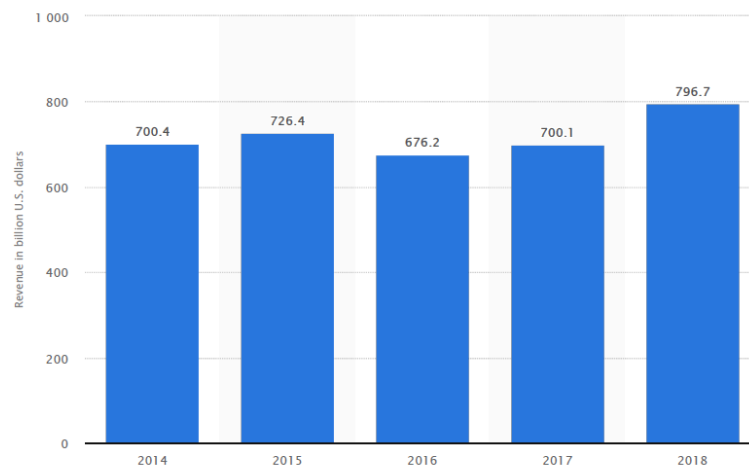
Details: United States; 2010 to 2018

© Statista 2019

Figure 1.3: Total operating revenues of the U.S. trucking industry from 2010 to 2018

Total revenue of the trucking industry in the United States from 2014 to 2018

(in billion U.S. dollars)



Details: United States; 2014 to 2018

© Statista 2019

Figure 1.4: Total revenue of the trucking industry in the U.S. from 2014 to 2018

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and to operate more efficiently. As a response to these challenges, we study in this thesis the centralized and decentralized logistics and transportation systems.

Centralization and decentralization describe the processes of the activities of an organization. In centralization, the activities particular those regarding planning and decision-making, framing strategy and policies become concentrated within a particular geographical location group. This moves the important decision-making and planning powers within the center of the organisation. In decentralization, the activities are distributed or delegated away from a central, authoritative location or group.

The words "Centralization" and "Decentralization" were first introduced to describe new government leadership structure in France since the end of 18th century. In the early 20th century America, decentralist movement was used as a response to the centralization of economic wealth and political power. "A decentralized system is where some decisions by the agents are made without centralized control or processing. An important property of agent systems is the degree of connectivity or connectedness between the agents, a measure global flow of information or influence. If each agent is connected (exchange states or influence) to all other agents, then the system is highly connected. " (Johnson, 1999). The concepts of decentralization have been applied to group dynamics and management science in private businesses and organizations, political science, law and public administration, economics, money and technology.

Decentralization in any area is a response to the problems of centralized systems. Government decentralization has both political and administrative aspects. Decentralization has been seen as a solution to problems like economic decline, government inability to fund services and their general decline in performance of overloaded services, the demands of minorities for a greater say in local governance, the general weakening legitimacy of the public sector and global and international pressure on countries with inefficient, undemocratic, overly centralized systems (Daun, 2006). In economics, decentralization allows efficient control or planning when each single agent or board can effectively survey all the relevant facts. Since 1970, some industries are being deregulated, like banking, trucking, airlines and telecommunications resulting generally in more competition and lower prices *.

*<https://www.cato.org/publications/commentary/shortcircuited>

1.2 Objectives and research methodology

In centralized logistics and transportation systems, multiple shippers or carriers collaborate closely to optimize the transportation operations through sharing transportation capacities or exchanging delivering tasks. However, real world transportation market is essentially distributed - decentralized. Self-interested shippers and carriers have private information and personal preferences. They behave strategically to achieve better efficiency and increase their own profits. In decentralized logistics and transportation systems, all independent actors interact in a self-interested nature.

This thesis is within the framework of an ANR project, "pi-co-modality". The partners are Centre de Gestion Scientifique de Mines ParisTech, DHL Service Central, INRIA Lille-Nord Europe and CNRS LAAS. For the European Commission, co-modality refers to a "use of different modes on their own and in combination" in the aim to obtain "an optimal and sustainable utilisation of resources". The pi-co-modality project is devoted to the design of co-modal chains between origins and destinations according to environmental and economic objectives. Co-modal is a term first used by the EU in 2006 and refers to the intelligent use of two or more modes of transport on their own and in combination to get the biggest benefit from each of them so that the overall journey is the most sustainable that it can be. This optimising in the use of resources has economic, environmental and societal benefits. The project is based on the concept of the Physical Internet (shortened by PI) ([Montreuil, 2011](#)) that breaks with previous established approaches. The metaphor with the digital internet is used to illustrate the key concepts. As digital packets on interconnected computer networks, the PI aims to develop a global logistics system based on the interconnection of logistics services networks to transfer goods between origins and destinations.

1.2 Objectives and research methodology

In the ANR project, the problem of designing multimodal sustainable chains is addressed from two perspectives. In the first case, we consider a centralized system or "system optimum" where a shipper is in charge of defining the "best" set of chains. In the second case, the system is shared between actors and decentralized. The shipper will specify the general framework (potential multimodal

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platforms to be used) and the origins and destinations of flows. Then, transportation companies will put out their offers, which will be considered according to a combinatorial auction mechanism. This will result in a shared logistics activity that optimizes the use of resources.

The goal of my thesis is to address the decentralized situation, and to extend the PI concept in a more realistic way. In order to achieve high level performance in decentralized environments, a potential auction center plays the role of market intermediary. Between the origin (i.e. shippers) and destination (i.e. customers), hubs act as goods transit center to increase the allocation efficiency of the system. All these actors are interacting with their own interests, their assets, their sub-networks and their independence.

The global goal of this dissertation is to rely on a "mechanism design" approach. More precisely, the market intermediary allocates bundles of lanes to set of carriers to define the solution between actors, and improve the performance of the mechanism driven by all actors. In other words, the main objective is to design an auction mechanism and a platform, to facilitate the matching of supply and demand between shippers and customers **leading to the most efficient global transportation resource allocation**. The solution should encourage shippers and carriers to use the auction mechanism rather to behave individually, such that all self-interested agents have a better interest to apply the solution designed by the platform rather than apply the basic self-interest solution.

The design of such a platform requires 3 steps,

- firstly, auction is defined to facilitate the matching between transportation demands and supplies, which refers to the **transportation procurement auctions**;
- secondly, **routing construction methods** is used to build bundle of lanes;
- and finally a **bidding generation problem** and **winner determination problem** are solved to determine the matching of supply and demand.

From a methodological point of view, we rely on the PI to modelize meshed network and on a "mechanism design approach" to define bundle of lanes for carriers, in order to increase the objective of the system; and then we consider a pricing-allocation bilevel optimization problem to determine the allocation of

lanes to carriers, in order to fully explore the interaction among shipper and carriers.

1.3 Outline of the dissertation

We next provide the description of the chapters, it consists of six parts:

- In chapter 2, we first introduce basic concepts for decentralized logistics and transportation systems. We next review the auction types used in transportation procurement and focus on Combinatorial Auctions (CAs). Finally, we define the bilevel optimization models and show why and how they can be used to improve the global solution for both shippers and carriers in CAs.
- In chapter 3, a detailed survey about Winner Determination Problem (WDP) is given to summarize the general and variants of the formulations for WDP. The complexity of the problem is analyzed. The exact and approximated algorithms are investigated in solving WDP accurately and efficiently, the performance of the algorithms is also compared with the most used benchmarks.
- In Chapter 4, we address the problem defined as Bundle Construction Problem (BCP) in a 5-phase procedure for CAs. Under the assumptions of CAs, each lane is defined as an origin-destination pair with time windows, combining distinct lanes into a single bid or constructing a bundle enables carriers to propose attractive prices, it will also lead to procurement cost reduction for shippers. We study the Bundle Construction Problem (BCP) under CAs specially for full truckload transportation procurement.
- In Chapter 5, we introduce the pricing-allocation bilevel model in CAs for full truckload transportation procurement. The auction-based Transportation Procurement Problem (TPP) involves solving the *Bid Generation Problem* (BGP) for carriers and the *Winner Determination Problem* (WDP) for shipper. In BGP, carriers place their bids (prices) for the most profitable bundles; in WDP, shipper allocate bundles to carriers based on their bids. To address this problem, we assume a market place - auctioneer

INTRODUCTION

representing shippers uses CAs to allocate lanes to carriers. We study the pricing-allocation problem (i.e. price-based BGP-WDP) under CAs specially for full truckload transportation procurement. The BGP and WDP are two of the main auction phases in the CAs. Even if they share strong relationship, it has not been investigated so far in the literature ([Gansterer & Hartl, 2017](#)). Our work is the first to merge BGP and WDP in a single bilevel formulation to model more accurate this interaction from a practical point of view.

- In Chapter 6, we extend the model given in Chapter 4 with a decentralized setting where the carriers at the upper level define prices in a competitive manner. The decentralized model can accurately describe the market environment when actors involved are selfish and non-cooperative. In this case, a multi-leader single-follower pricing-allocation bilevel model is given and it can be solved by best-response strategy under multiple round CAs.
- Finally, in Chapter 7, we summarize the work of this dissertation, and give perspectives and future extensions.

Chapter 2

State of the art of Decentralized Logistics and Transportation Systems

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2. STATE OF THE ART OF DECENTRALIZED LOGISTICS AND TRANSPORTATION SYSTEMS

The objective of this chapter is to introduce basic concepts and information for decentralized logistics and transportation systems. We review the auction types used in transportation procurement and focus on CAs. Next, we address the bilevel programming and show why and how it can be used to improve the global solution for both shippers and carriers in CAs.

2.1 Decentralized logistics and transportation systems

Logistics activities considered in this thesis involve the various stakeholders classified into five groups of actors and two main facilities,

Five actors:

- **shippers**, are the owner and provider of the necessary customer goods, they provide logistics tasks to get their components or goods transported to their customers;
- **3PL or Third Party Logistics**, refers to the outsourcing of logistics activities, ranging from a specific task such as trucking or marine cargo transport to broader activities serving the whole supply chain such as inventory management, order processing and consulting*;
- **4PL or Fourth Party Logistics**, refers to a party who works on behalf of client to do contract negotiations and management of performance of 3PL providers including the design of the whole supply chain network and control of day-to-day operations;
- **carrier**, also mentioned as logistics service provider (Natalia *et al.*, 2016), is a provider institution freight forwarder (transporter, freight forwarders, shipping liner) from the place of origin of goods (shipper) to its destination (consignee), storage of goods and services (warehousing, fumigation, and so on). The origin of the goods could have come from the manufacturer, supplier, while the destination to consumers, distributors, or manufacturers;

*<http://www.supplychainopz.com/2012/04/what-is-logistics-and-supply-chain-management.html>

2.1 Decentralized logistics and transportation systems

- **customers**(Natalia *et al.*, 2016), "logistics users who need goods both for the production process as well as for consumption. customers can determine the type and quantity of goods to be purchased, from whom and where the goods are purchased and where the goods were delivered".

Two facilities:

- **The logistic auction center** provides logistics services and holds transportation auctions for bidding agents and auctioneers;
- **The hubs** are storing areas to mutualise deliveries while providing additional functions like repackaging, information and material transaction. Moreover, the hubs also provide
 - current logistics information such as demand and supply;
 - tools to monitor cargo movement by all modes of transportation;
 - ancillary services such as finance and insurance.

For better understanding, in auction-based transportation procurement, we also give the following notations,

- *Shippers* or a *market intermediary* represent shippers is the *auctioneer* in the auction language;
- *Carriers* are service providers and *bidders*;
- A *link* is a physical delivery route connecting two locations directly;
- A *lane* is an origin destination pair on which shippers have loads to move; a lane may include service time or capacity requirement, etc... For example, shipper *A* has a load need to be transported from Paris to Lyon within the date of 01/08/2019 - 03/08/2019;
- A bid is a set of lanes called lane bundle and a bidding price. For example: Carrier *B* provides service on Paris to Lyon lane and Lyon to Nice lane with a price *b*.

2. STATE OF THE ART OF DECENTRALIZED LOGISTICS AND TRANSPORTATION SYSTEMS

A general framework for decentralized logistics and transportation systems is shown in Figure 2.1. Without loss of generality, we assume that all served lanes are long distance ones, which implies that the transportation cost between the shippers and hubs can be neglected and routing through hubs could be beneficial for the shippers. In decentralized environments, it is also assumed that all the agents (shippers and carriers) are selfish and each of them chooses his strategy to increase his own profit.

The following sequence of events take place in the transportation auction center:

- Market intermediary receives tasks from shippers and repackages the deliveries at the hubs and then announces which lanes (a original-destination pair is defined as a lane) will be auctioned;
- Carriers place bids on the lanes being auctioned, bids may combine different adjacent lanes involve a single or multiple shippers;
- Market intermediary receives the bids and determines which lanes each carrier wins.

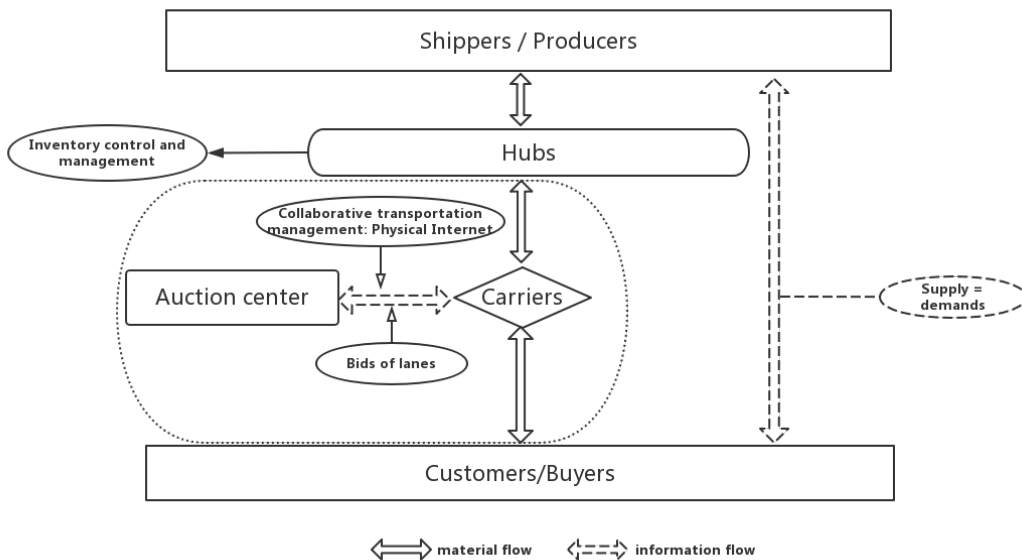


Figure 2.1: General framework for decentralized logistics and transportation systems.

2.1 Decentralized logistics and transportation systems

Unlike traditional transportation systems where the deliveries are separately flowed from shippers to customers, the considered systems favor mutualisation of resources among actors and thus reduce the cost. For example, for a customer with many orders from multiple providers, joining their packages at the hub such that a single package is delivered to customers can reduce the deliveries costs. Moreover, shippers can store all the customers' orders in the hubs periodically, which will reduce the frequency of the transportation services in the network i.e. reduce the less than full truckload shipping from shippers to hubs.

In conclusion, the next advantages of using an auction center and hubs are:

- the repackaging can reduce the number of deliveries from the shippers to customers;
- the mutualisation of deliveries thanks to the storage can reduce the Less Than Truckload Shipping (LTL) and the frequency of the transportation services in the network.

Example in Figure 2.2 can be seen as a auction-based decentralized logistics and transportation system, it implement how information and materials move in a food supply industry.

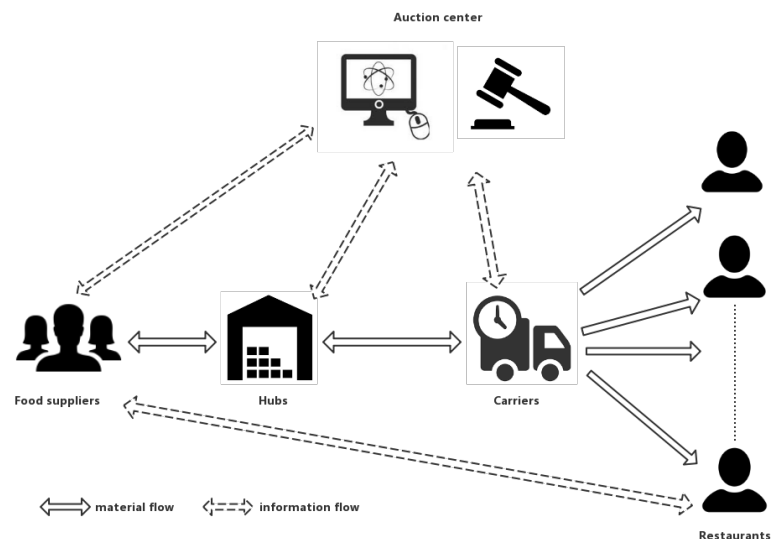


Figure 2.2: Information and materials flow in a food supply industry.

2.2 Transportation procurement auctions

Transportation procurement problem (TPP) is generally the problem of determining transportation and exchanging relationships across a transportation market, it consists of shippers, carriers and a third-party exchange service provider. Most of shippers use auctions to procure transportation services with an origin/destination pair defined as a lane, a volume to be shipped on this lane, and some other information on shipping conditions, time windows, specific equipments, etc.

Transportation procurement auction starts with a call for quotation, initiated by the shipper (or third-party logistics on behalf of the shippers), followed by bidding (bid generation) of various carriers interested in the offer. Carriers can either bid for each lane individually or a bundle called combinatorial bid. After receiving bids from carriers, the shippers evaluate the submitted bids and find out the winning bids (carrier assignment). Major research work is carried out with respect to both the **bid generation** and **carrier assignments** aspects. Related reviews on transportation procurement problems based on Bid Generation Problem (BGP), Carrier Assignment Problem (CAP) and Collaboration are provided in [Ramanatan *et al.* \(2015\)](#). In the review of [J.Meixell & Norbis \(2008\)](#), the authors investigate the transportation choice research (mode choice and carrier selection). Their work allow us to better understand the transportation procurement market and explore the future study.

In the next section, I will first review the main auction types, then I will focus on auctions for transportation procurement with recent papers on these subjects.

2.2.1 Auction types

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

- **Single item auctions:** This type of auction is useful for selling/buying a single unit of an item. Although it is used in the real market, in terms of computation approach is not important. English auction, Dutch auction

2.2 Transportation procurement auctions

and first (or second) price sealed-bid auctions are good examples of these traditional auctions.

- **Multi-unit auctions:** Auctions involving the sale of different items are named multi-unit auction. Transportation domain can be a good example in multi-unit auctions area. In this auction, a buyer and multiple sellers wish to exploit economies of scale by using a volume discount auction.
- **Vickrey auction:** Vickrey auction is an auction for multiple similar items. Bidders submit their demand simultaneously. Each bidder wins the demanded item at the clearing price, and pays the opportunity cost of its winnings. If there is only an item for bidding, the vickrey auction will be second-price auction. If the auction performs for non-identical item, the Vickrey auction referred to as generalized Vickery auction (GVA) or Vickery-Clarke-Groves (VCG).
- **Generalized Vickrey Auction (GVA):** GVA is single round second-price sealed-bid combinatorial auction, in which the highest bid will be the final winner, but pays the second highest bidding price. Therefore, a winning bidder can never affect the paid price. In addition, there is no incentive for any bidder to misrepresent its value. GVA is known as one of the most efficient auctions.
- **Iterative bundle auction:** Iterative bundle auctions are indirect implementations of GVA. This type of auction is reputable for addressing computational and informational complexity of GVA. In this class of auction, the agents are allowed to reveal essential information as the auction progressed. However the exact and private information has to be kept uncover by the agents. This auction is designed for general combinatorial allocation (CA) problem.
- **Sequential and simultaneous auctions:** price bundles as the sum of each individual line, and assume that a set of preferred resources are auctioned in sequence. Agents bid on resources considering the past successes, failures, prices, and etc. The main application of this class of auction is in

2. STATE OF THE ART OF DECENTRALIZED LOGISTICS AND TRANSPORTATION SYSTEMS

combinatorial or simultaneous items. Multiple goods sell in separate markets at the same time. The agents have to interact to separate markets in order to achieve a combinatorial of resources to accomplish their tasks.

2.2.2 Auctions for transportation procurement

Generally, the Transportation Procurement Problem (TPP) is the problem of setting transportation service prices, delivery timing and quantity, and controlling costs and capacity to reduce empty movements and improve market efficiency (Song & Regan, 2003b) etc. Auction-based TPP has gain a great deal of attention in transportation research. The most used auction type for transportation procurement can be summarized as follows,

- **Sequential auctions:** In sequential auctions marketplaces, demands of shippers arrive randomly over time and each arrived demand is successfully auctioned before another one comes in (Figliozzi, 2006; Figliozzi *et al.*, 2007), these studies on sequential auctions are usually set in dynamic and stochastic environments.
- **Combinatorial Auctions (CAs):** CAs allow a single bid for a set of distinct lanes from a single or multiple shippers (Song & Regan, 2003b; Wang & Xia, 2005). CAs are essentially simultaneous multi-unit auction paradigms, carriers have to maximize their capacity utilization and balance delivery requirements such as distinct destinations and arrival time windows. Combining distinct lanes into a single bid enables carriers to achieve the economics of scope (Caplice & Sheffi, 2003), which will also lead to procurement cost reduction for shippers (Caplice & Sheffi, 2003).
- **Double auctions:** A double auction scheme involves a third-party auctioneer, i.e., market clearing broker. An important benefit of double auction is that it allows simultaneous bidding from both buyers and sellers, and clears the market one at a time based on the received asks and bids. Under double auctions, the existing results related to transportation procurement problem appeared in Cheng *et al.* (2016); Xu & Huang (2014b).

Sequential auctions and Double auctions can be seen as special cases of CAs when we consider multiple rounds and market clearing factors. Due to exclusive advantages of **CAs**, it is used throughout this dissertation.

2.2.3 Bidding language for transportation procurement combinatorial auctions

In an auction, bidders have to formulate bids according to their private preferences, information, and bidding strategies (Nisan & Ronen, 1999). A bidding language in the auction defines the standard way (the format of the communicated messages and the interpretation) that the bidders are allowed to formulate their bids. In transportation procurement, it refers to how carriers communicate their true valuation of the lanes, we give three inter-relationships between lanes as defined in Song & Regan (2003a):

Definition 2.1 *Denote $v(A)$ as a carrier's true valuation of a set of lanes A if and only if these lanes are assigned, two disjoint sets of lanes A and B are:*

- *Complementary: if $v(A) + v(B) > v(A \cup B)$;*
- *Substitutable: if $v(A) + v(B) < v(A \cup B)$;*
- *Additive: if $v(A) + v(B) < v(A \cup B)$.*

In transportation logistic network, a set of lanes is complementary to another set of lanes when it can refill each others' empty movements; a set of lanes is substitute to another set of lanes when one of these two sets can be contained by the other one; a set of lanes is additive to another set of lanes when they do not exist connection. For example, a lane from Paris to Lille is a complementary to a lane from Lille to Paris, as they can reduce the empty backhaul; a set of lanes from Paris to Lyon, Lyon to Marseille is a substitute to the direct lane from Paris to Marseille; and the lane from Paris to Lille is additive to the lane from Lyon to Marseille as share no relation.

For CAs, bidders need to make sets of bids for "bundles" of items, where the bid for the different bundles can be either exclusive or non-exclusive. The basic bidding languages of this form are classified and given in Nisan (2000, 2006).

Hereafter in this section, we give the most general used bid form in CAs.

Definition 2.2 (Atomic bids) *Each bidder can submit a pair (S, p) where S is a subset of the items and p is the price that he is willing to pay for S . Thus the valuation of a set T is $v(T) = p$ for $S \subseteq T$ and $v(T) = 0$ otherwise. Such a bid is called an atomic bid.*

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Atomic bids are called single-minded bids in [Lehmann et al. \(2002\)](#). It is clear that many simple bids cannot be represented by this language.

Definition 2.3 (OR bids) *Each bidder can submit an arbitrary number of atomic bids, i.e., a collection of pairs (S_i, p_i) , where each S_i is a subset of the items, and p_i is the maximum price that he is willing to pay for that subset.*

Under OR bids, each bidder is willing to obtain any number of disjoint atomic bids for the sum of their respective prices. Thus an OR bid is equivalent to a set of separate atomic bids from different bidders. More formally, for a valuation $v = (S_1, p_1)OR\dots OR(S_k, p_k)$, the value of $v(S)$ is defined to be the maximum over all possible valid collections W , of the value of $\sum_{i \in W} p_i$, where W is valid if for all $i \neq j \in W, S_i \cap S_j = \emptyset$.

Proposition 2.4 *OR bids can represent all bids that don't have any substitutabilities, i.e., those where for all $S \cap T = \emptyset, v(S \cup T) \geq v(S) + v(T)$, and only them.*

Definition 2.5 (XOR bids) *Each bidder can submit an arbitrary number of pairs (S_i, p_i) , where S_i is a subset of the items, and p_i is the maximum price that he is willing to pay for that subset.*

Under XOR bids, each bidder is willing to obtain at most one of these bids. More formally, for a valuation $v = (S_1, p_1)XOR\dots XOR(S_k, p_k)$, the value of $v(S)$ is defined to be $\max_{i|S_i \subseteq S} p_i$.

Proposition 2.6 *XOR bids can represent all valuations.*

XOR is formally defined from [Sandholm \(2002\)](#), and it is widely used in most CAs literature as it can represent OR bids and also those with substitutabilities.

In [Nisan \(2006\)](#), the author also discuss the combinations of OR and XOR to represent more desirable simple valuations.

Definition 2.7 (OR of XORs bids) *Each bidder can submit an arbitrary number of XOR bids, as defined above.*

Implicit here is that he is willing to obtain any number of these bids, each for its respectively offered price.

Definition 2.8 (XOR of OR bids) *Each bidder can submit an arbitrary number of OR bids, as defined above.*

Implicit here is that he is willing to obtain just one of these bids.

2.3 Combinatorial Auctions (CAs) for transportation procurement problem

Over the past two decades, CAs has gained more and more attentions both in theoretical and practical studies (Peter *et al.*, 2006), which allow bidders to bid on combinations of items as a packages instead of bidding only on individual items. The advantage of CAs is that the bidders can fully express their preferences when items are complements and substituents due to the economies of scope and economies of scale, in such a sense, the bidders can generate more profit or save more cost.

While in a competitive transportation procurement system, if carriers can combine multiple lanes as a tour or a continuous move, they can decrease their empty mileage and thereby reduce cost (Chen *et al.*, 2009) or generate greater profits (Chang, 2009; Jothi Basu *et al.*, 2015). Due to the synergies available on the transportation pathways (Triki, 2016; Wang & Wang, 2015; Xu & Huang, 2014a,b), CAs has attracted increasing attentions in transportation procurement as it allows carriers to submit bundle bids that can express their preferences when they group transportation lanes into packages (Sheffi, 2004a; Triki *et al.*, 2014).

In transportation procurement, CAs generally follows a 5-phase procedure (Berger & Bierwirth, 2010), see Figure 2.3:

- Carriers determine request lanes and put them into the auction pool, request lanes are selected based on carriers' time and truck capacity availability;
- Bid Generation Problem (BGP): Auctioneer (Shipper or Third-party logistics - 3PL) generates bundles of requests and shows them to the carriers, a request bundle is generally a feasible path tour respecting each carrier's resource constraints;
- Bid Generation Problem (BGP): Carriers give their bids for the offered bundles;
- Winner Determination Problem (WDP): Auctioneer allocates bundles to carriers based on their bids;
- Gained profits are distributed among the carriers.

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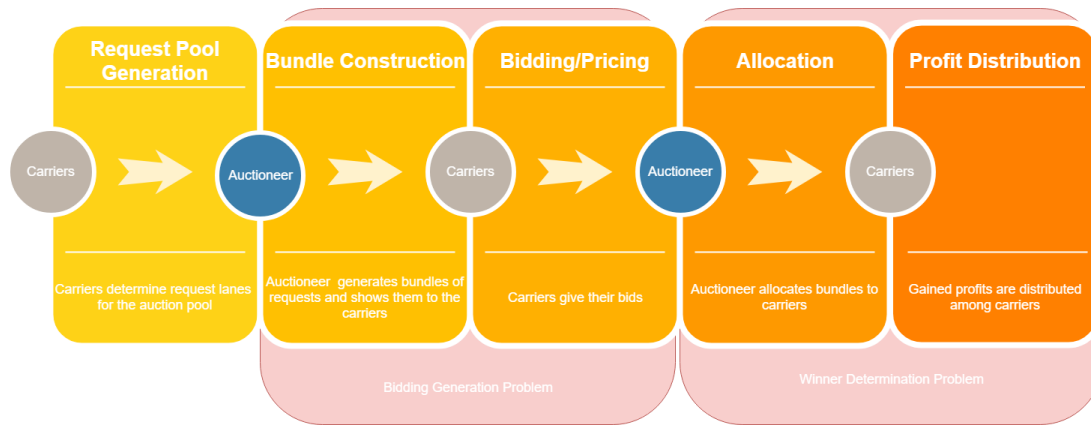


Figure 2.3: 5-phase procedure for CAs.

As mentioned in [Xia *et al.* \(2004\)](#), the ideal auction mechanism for CAs should provides the following three features:

- An efficient winner determination mechanism;
- Incentive compatible bid pricing mechanism;
- A way to determine imputed prices for goods.

The following of this section will review the above presented Bidding Generation Problem (BGP) and Winner Determination Problem (WDP) in transportation problem.

2.3.1 Bidding generation problem for transportation procurement problem

CAs has attracted increasing attention in transportation procurement market because of the synergies * available on the transportation pathways ([Triki, 2016](#); [Wang & Wang, 2015](#); [Xu & Huang, 2014a,b](#)) as transportation request lanes can be grouped into packages or bundles of various products ([Sheffi, 2004a](#); [Triki *et al.*, 2014](#)), request bundle is defined as a path tour from one location to another.

In the transportation procurement, the carriers' major goal is to discover and take advantage of inter-dependencies in their transportation operations, and then

*The synergies means that the traveling and other operating costs associated with a set of lanes are lower than the sum of the traveling and other operating costs per lane associated with each individual lane.

2.3 Combinatorial Auctions (CAs) for transportation procurement problem

determine the optimal packages to bid for. A carrier's pricing decision involves choosing right prices for right transport request bundles in order to maximize his profit, this is known as price-based revenue management (Talluri & Van Ryzin, 2006; Ting* & Tzeng, 2004). It consists two decision making problems as we define as two phases. In first phase, potential tours (bundles, bids of requests) are determined that a carrier could bid for. Each tour is constructed so that all relevant operating constraints can be met, this problem is defined as Bundle Construction Problem (BCP). In second phase, incentive pricing strategies are employed that each carrier could win his desired bids, this problem is defined as Bundle Pricing Problem.

An overview of the carrier's Bidding Generation Problem is as follows:

Max	Total utility	(2.1)
subject to	Each request lane can be covered at most once	(2.2)
	Bidding language constraints: XOR or OR	(2.3)
	Connection constraints of the path tour	(2.4)
	Resource constraints for carriers: trucks need to return to a given location, driving distance/time limitation, etc...	(2.5)
	Resource constraints for trucks: capacity limitation	(2.6)
	Resource constraints for request lanes: served on time, etc...	(2.7)
	Other operating constraints	(2.8)

(2.1) describes the total utility or profit that a carrier can gain through severing request bundles, which is generally defined as the served request bundles' price minus the serving cost; (2.2) says each request lane can be at most served by one carrier; (2.3) is the bidding language constraints mentioned in Section 2.2.3; (2.5) are the resource constraints for carriers, such as, the trucks must return to the depot or to a given location, the driving distance or time must under a given limitation, etc...; (2.6) describes the trucks' capacity constraint for less than truckload case; (2.8) gives the information and constraints for the request lanes, as some request lanes must be served during a certain time interval or other

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requirement; (2.8) supplements the specific constraints for a given model, such as shipment uncertainty or service quality level, etc...

2.3.1.1 Bundle construction problem

Bundle Construction Problem (BCP) in transportation procurement is described as follows, for given set of carriers, generate - find and select - feasible bundles with high quality respecting the carriers' flexibility and resource budget. Here, a request lane is defined as a pick-up/delivery location pair with resource constraints (time, capacity, etc...). The problem of defining feasible bundles is a problem of route-building or route-construction problem as introduced in [Baker & Schaffer \(1986\)](#). In BCP, not all lane requests need to be visited, indeed, the carriers only have to find all the bundles that they can handle and make profit. This problem is also recognized as an Orienteering Problem (OP) with resource constraints. The OP problem is a route-construction problem in which a subset of requests are determined to visit, such that the total profit/score are maximized and the resource constraints is not exceeded ([Gunawan *et al.*, 2016](#)).

2.3.1.2 Bundle pricing problem

In auction-based transportation procurement, carriers are often driven by economies of scope and proposing right price in order to win lanes. While in most of literature of Bidding Generation Problem, marginal prices are used to generation bundles and then determine the lane allocation. In a more realistic setting, price is a main factor that can largely effect the shippers and carriers' decision and the final profit, determining prices for individual goods is also valuable because ([Xia *et al.*, 2004](#)):

- "they help explain the auction result - why a certain bid lost and another won";
- "they can serve as a price guide for future auctions".

Thus, when and how to price the bundles should also be discussed here.

In the TL industry, carrier charges a fixed cost for each truck whether it is fully or partially loaded, he may consider some factors to adjust the price (or bid), for example asymmetric requests in a truck's round-trip ([Zhou & Lee, 2009](#)),

2.3 Combinatorial Auctions (CAs) for transportation procurement problem

daily scheduling (Mes & Van der Heijden, 2007), real-time request learning and forecasting (Lin, 2006), competitor behaviour (Toptal & Bingöl, 2011), or synergy between lanes of long-term contracts and spot contracts (Kuyzu *et al.*, 2015). Under this situation, fill rate or request size is not taken into account.

While in the LTL industry, carrier charges a shipping price for each unit (per palette/kg) of the requests. There are only few research focusing on the LTL pricing problem (Dai & Chen, 2011; Douma *et al.*, 2006; Wang & Kopfer, 2011), even less focuses on dynamic and stochastic pricing. In Qiao *et al.* (2016), a dynamic pricing model was studied under a specific context - the Physical Internet (PI). And in Toptal & Bingöl (2011), the replenishment problem of a retailer and the transportation pricing problem of a truckload carrier under the presence of two carriers (one TL carrier and one LTL carrier) was studied.

In a dynamic environment, where transport requests with different volumes and/or destinations arrive over time, carriers can adjust their pricing policies within a given time, taking into account the status and the arrival of requests in real time to maximize their expected profits, this is known as dynamic pricing decision problem (Lin, 2006; Talluri & Van Ryzin, 2006).

However, in the literature, as most of the literature mentioned above, TL carriers may consider some factors to adjust the price (or bid), but the pricing strategies are studied heavily depend on the requests/demands in Lin (2006); Mes & Van der Heijden (2007); Qiao *et al.* (2016); Zhou & Lee (2009), there is less competition mentioned. To remedy this, Toptal & Bingöl (2011) study the competition among TL and LTL carriers, and Kuyzu *et al.* (2015) address the competition among long-term contracts and spot contracts.

Neglecting the transportation procurement perspective, Xia *et al.* (2004) discuss also different pricing strategies in CAs, which defined the winning prices or market clearing prices as follows,

Definition 2.9 *For CAs, a set of item prices is called **market clearing** or **equilibrium** if all the winning bids are greater than or equal to the total price of the bundle items and all the losing bids are less than or equal to the total price of the bundle items.*

The bundle pricing approaches and individual pricing together with their advantages and disadvantages are discussed and summarized in the paper Xia *et al.* (2004), which we will not mention it here again.

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2.3.2 Winner determination problem for transportation procurement problem

The concept of WDP is expressed as follows: consider a set of bids in a CAs, find an item-conflict-free allocation to bidders (not all items need to be allocated) such that the auctioneer's revenue is maximized or the auctioneer's cost is minimized.

Given $N = \{1, \dots, n\}$ the set of bidders and $M = \{1, \dots, m\}$ the set of items. A bundle S is a subset of items in M : $S \subseteq M$. Let $\mathcal{F}_i \subseteq M$ be the set of bundles for which bidder i submits an atomic bid, and $\mathcal{F} = \mathcal{F}_1 \cup \dots \cup \mathcal{F}_n$ the set containing all the bundles demanded by at least one of the bidders. Each bidder i can give a bundle S an atomic bid $v_i(S)$ i.e., the highest price that bidder i is willing to pay for bundle S .

The items are allocated through variables $x_i(S) \in \{0, 1\}$: it equals to 1 when bidder i get bundle S . An allocation $(x_i(S) | i \in N, S \subseteq M)$ is said to be feasible if it allocates no item more than once:

$$\sum_{i \in N} \sum_{S \subseteq M, S \ni j} x_i(S) \leq 1 \quad \text{for all } j \in M, \quad (2.9)$$

and at most one bundle to every bidder

$$\sum_{S \subseteq M} x_i(S) \leq 1 \quad \text{for all } i \in N. \quad (2.10)$$

OR and *XOR* bidding languages are widely used in this problem and will be presented here, we give two refinements of *WDP*, called *WDP_{OR}* and *WDP_{XOR}* respectively. In both frameworks, bidders provide atomic bids for the bundles.

The WDP problem is defined as follows (De Vries & Vohra, 2003),

Definition 2.10 Winner Determination Problem (WDP)

Given bids $v_i(S), i = 1, \dots, n$ and $S \in \mathcal{F}$, the winner determination problem is the problem which determines

$$x \in \operatorname{argmax} \left(\sum_{i \in N} v_i(S) x_i(S) \mid x \text{ is a feasible allocation} \right). \quad (2.11)$$

In the **OR bidding language**, the atomic bids for bidder i can be seen as follows, i is willing to accept any combination of pairwise disjoint atomic bids

2.4 Bilevel programming and its application to CAs

a price equal to the summation of the disjoint bid prices. In this case, disjoint atomic bids can be combined as one bid, multiple bids can be given to one bidder as soon as it is feasible, constraint (3.2) is thus omitted, see Daniel *et al.* (2006).

Definition 2.11 (WDP_{OR})

Given a set of bids in the OR bidding language, with atomic bids on sets in \mathcal{F}_i for every bidder i , WDP_{OR} is the problem which computes

$$x \in \operatorname{argmax} \left(\sum_{i \in N} v_i(S)x_i(S) \mid x \text{ satisfies (3.1)} \right). \quad (2.12)$$

In **XOR bidding language**, the atomic bids for bidder i can be seen as follows, bidder i can only receive at most one atomic bid.

Definition 2.12 (WDP_{XOR})

Given a set of bids in the XOR bidding language, with atomic bids on sets in \mathcal{F}_i for every bidder i , WDP_{OR} is the problem which computes

$$x \in \operatorname{argmax} \left(\sum_{i \in N} v_i(S)x_i(S) \mid x \text{ satisfies (3.1) and (3.2)} \right). \quad (2.13)$$

For the detailed review of WDP problem, we refer Chapter 2 for the WDP survey.

2.4 Bilevel programming and its application to CAs

Bilevel optimization problems are optimization problems involving two independent decision makers with a hierarchical structure, where some decision variables in one optimization problem (the upper level problem) are constrained to be optimal in a second optimization problem (the lower level problem). It describes the problem as follows, at the upper level, the *leader* makes decisions; then, at the lower level, the *follower* reacts optimally to the leader's decision. Originally the problem was introduced in an economic setting in Stackelberg *et al.* (1952) as a sequential game called *Stackelberg game*. The literature on bilevel programming from both economical and mathematical perspectives has been largely investigated since then, more recently, the book Dempe (2018) provides a detailed survey about the theory, algorithms and applications on bilevel optimization.

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2.4.1 Problem description

In a bilevel optimization problem, both leader and follower aim to optimize their own utilities by determine their own set of variables. Let $x \in X$ and $y \in Y$ denote the decision variable vector of the leader and the the follower respectively, with X and Y closed and nonempty. Then, for a given decision x of the leader, the follower has to solve a optimization problem as follows,

$$\min_y f(x, y) \quad (2.14)$$

$$\text{s.t. } y \in Y \quad (2.15)$$

$$g(x, y) \leq 0 \quad (2.16)$$

$$h(x, y) = 0 \quad (2.17)$$

where $g(x, y)$ and $h(x, y)$ are set of inequality and equality constraints functions.

The follower's optimal/rational reaction yield a solution set mapping:

$$y(x) := \{y \in \operatorname{argmin} f(x, y) \mid y \in Y, g(x, y) \leq 0, h(x, y) = 0\} \quad (2.18)$$

We define then the graph of y , it give the optimal/rational response $y(x)$ of the follower to any of the leader's decision x :

$$\Phi(x) := \{(x, y) \mid x \in X, y \in y(x)\} \quad (2.19)$$

On the leader's side, he optimize his objective function $F(x, y(x))$ by taking into account $y(x)$ is an optimal response of the follower to x , where x satisfies also a set of inequality constraints $G(x, y(x))$ and equality constraints $H(x, y(x))$. The leader's problem is defined as

$$\min_x \{F(x, y(x)) \mid x \in X, G(x, y(x)) \leq 0, H(x, y(x)) = 0, (x, y(x)) \in \Phi(x)\} \quad (2.20)$$

Thus the global bilevel programming problem (BLPP) can be represented as

the form:

$$\min_x F(x, y(x)) \tag{2.21}$$

$$\text{s.t. } G(x, y(x)) \leq 0 \tag{2.22}$$

$$H(x, y(x)) = 0 \tag{2.23}$$

$$y(x) = \operatorname{argmin}_y \{f(x, y) \mid g(x, y) \leq 0, h(x, y) = 0\} \tag{2.24}$$

Overall, the *relaxed feasible set* for BLPP is defined as $\Omega = \{(x, y) : G(x, y) \leq 0, H(x, y) = 0, g(x, y) \leq 0, h(x, y) = 0\}$, and the *inducible region* or *feasible set* for BLPP is $IR = \{(x, y) : (x, y) \in \Omega, (x, y) \in \Phi(x)\}$. The inducible region is the set the leader may optimize.

2.4.2 Optimistic and pessimistic bilevel formulation

The bilevel problem (Colson *et al.*, 2007) has a natural interpretation as a non-cooperative game between two levels. Players at the upper level (leaders) choose his decision x first, after seeing the x , players at lower level (followers) responds with a decision y , as defined in Equation (2.18), there may exist several optimal solutions at the lower level for fixed leader decisions. Since the leader cannot anticipate the follower's decision, the constraint must be satisfied for any rational decision of the follower, that is, for any feasible decision x that optimizes the follower's objective function. This statement leads to a optimistic/pessimistic bilevel problem where the leader have to face the best/worst case that may happen to him. Two main strategies have been originally proposed by Loridan & Morgan (1996) to explore these two cases.

2.4.2.1 Optimistic formulation

As it says in word, under optimistic formulation, the leader is in a optimistic situation, for a given decision x , he assumes that the follower will always select the solution in $\Phi(x)$ that is most favorable to the leader. In this case, Problem (2.20) is thus:

$$\min_x \{ \min_{y(x)} F(x, y(x)) \mid x \in X, G(x, y(x)) \leq 0, H(x, y(x)) = 0, (x, y(x)) \in \Phi(x) \} \tag{2.25}$$

2. STATE OF THE ART OF DECENTRALIZED LOGISTICS AND TRANSPORTATION SYSTEMS

It describes the fact that the leader chooses the best solution $y \in y(x)$ for any given decision x . The general formulation of optimistic bilevel formulation is as follows:

$$\min_x \min_{y(x)} F(x, y(x)) \quad (2.26)$$

$$\text{s.t.} \quad G(x, y(x)) \leq 0 \quad (2.27)$$

$$H(x, y(x)) = 0 \quad (2.28)$$

$$y(x) = \operatorname{argmin}_y \{f(x, y) \mid g(x, y) \leq 0, h(x, y) = 0\} \quad (2.29)$$

As optimistic formulation gives the leader the selection power to the follower's solution pool, this problem are also referred as *strong* Stackelberg games ([Loridan & Morgan, 1996](#)).

2.4.2.2 Pessimistic formulation

While in pessimistic case, the leader consider the worst case that it may happen to him, that is, the follower is always going to react optimally to leader's decision x that is least favorable to the leader.

In this case, Problem (2.20) is thus:

$$\min_x \{ \max_{y(x)} F(x, y(x)) \mid x \in X, G(x, y(x)) \leq 0, H(x, y(x)) = 0, (x, y(x)) \in \Phi(x) \} \quad (2.30)$$

It describes the fact that the leader chooses the worst solution $y \in y(x)$ for any given decision x . The general formulation of pessimistic bilevel formulation is as follows:

$$\min_x \max_{y(x)} F(x, y(x)) \quad (2.31)$$

$$\text{s.t.} \quad G(x, y(x)) \leq 0 \quad (2.32)$$

$$H(x, y(x)) = 0 \quad (2.33)$$

$$y(x) = \operatorname{argmin}_y \{f(x, y) \mid g(x, y) \leq 0, h(x, y) = 0\} \quad (2.34)$$

When a pessimistic formulation is solved, that is the worst-case scenario

solved, the leader can guarantee the least objective that he can get, it leads to a *weak* Stackelberg game (Loridan & Morgan, 1996).

2.4.2.3 Rewarding and deceiving solutions

As follower in reality does not going to react in the predicted way - the optimistic or pessimistic - with lack of communication or private information, and the choice of the follower influences the leader's objective value, thus, *rewarding* and *deceiving* solutions are also introduced as alternative solutions of the bilevel problem (Alves & Antunes, 2016).

- **Rewarding solution:** the leader's decisions are determined with the pessimistic formulation, but the solution chosen by the follower is the most favorable for the leader.
- **Deceiving solution:** the leader's decisions are determined with optimistic formulation, but the solution chosen by the follower is the least favorable for the leader.

For the leader, the various solutions are ordered as follows:

$$\text{deceiving} \leq \text{pessimistic} \leq \text{rewarding} \leq \text{optimistic}$$

2.4.3 Bilevel resolution

Bilevel programming belongs to the class of NP -hard problems, which means that no polynomial time algorithms exist for solving it unless $P = NP$ (Bard, 2009). Even with the simplest form of a bilevel problem, where all constraints and objectives are linear, is NP -hard (Ben-Ayed & Blair, 1990; Labbé *et al.*, 1998). In general, the feasible region of the leader is nonconvex, and can even be disconnected or empty (Colson *et al.*, 2005). This is the reason why there do not exist many effective algorithms for solving these problems, and even less for pessimistic case.

Effectively solving bilevel problems heavily depends on the nature form of (2.21)-(2.24). When the follower's problem is convex for a given fixed decision from the leader and the constraint qualification is satisfied (e.g. Slater's condition), the lower level problem can be replaced by its Karush-Kuhn-Tucker (KKT)

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optimality conditions in the leader's problem (Bard & Moore, 1990; Edmunds & Bard, 1991; Gümüş & Floudas, 2001; Hansen *et al.*, 1992; Júdice & Faustino, 1988). This yields a *mathematical problem with equilibrium constraints* (MPEC) that widely developed to solve bilevel problems. However, Dempe & Dutta (2012) show that in optimistic case, global and local optimal of the bilevel problem and the MPEC do not always correspond. The global optimal solutions of the MPCC correspond to global optimal solutions of the bilevel problem provided the lower-level problem satisfies the Slater's constraint qualification, but the local optimal are complicated to verify. Thus, Dempe (2019) use a relaxation of the bilevel problem in two constraints in which a sequence of locally optimal solutions of the relaxed problems converges to a point which is related to a locally optimal solution of the bilevel optimization problem. If the lower-level problem is a linear one, relaxation of only the complementarity constraint is sufficient. The correspondence of optima in the pessimistic case has been discussed in Aussel & Svensson (2019); Dempe *et al.* (2019).

2.4.4 Bilevel application and its application to CAs

Despite the problem is hard to solve due to its complexity, bilevel problems and even multi-level problems are attracting more attentions as they allow to model complicate real-life problems which actors involved has to make their own decisions sequentially and the decisions made can influence each other. This includes problems in the domain of transportation, economics, decision science, business, engineering, environmental economics etc.

Bilevel optimization was first introduced in the field of game theory by a German economist Freiherr von Stackelberg who published *Market Structure and Equilibrium* in 1934 (Von Stackelberg, 2010), in a work of great originality and richness, he described and analyzed a market situation in which the leader firm moves first and the follower firms then move sequentially (Stackelberg *et al.*, 1952). The bilevel setting were soon used for military propose (Bracken & McGill, 1973) where the leader has to determine a resource allocation - weapons owned by the follower - problem.

Examples of problems that are adequately modeled with bilevel programming including but not limited to defense applications, electricity markets and

2.4 Bilevel programming and its application to CAs

networks, facility location and production problem, problems over networks, interdiction problems, price setting problems, resource allocation, etc... See [Dempe \(2018\)](#) for a detailed list and publications.

In this dissertation, the bilevel setting is employed to build a pricing-allocation model in CAs. Pricing problems have composed a class of problems that fit ideally bilevel framework when player/follower in the system is sensitive to the price changes and will react differently, then the price proposer/leader has to determine an optimal pricing strategy with knowing the follower's reaction. Pricing bilevel models has been studied in [Brotcorne *et al.* \(2001\)](#); [Heilporn *et al.* \(2010\)](#); [Labbé *et al.* \(1998\)](#) as toll-setting problem, in [Afşar *et al.* \(2016\)](#); [Aussel *et al.* \(2017, 2019\)](#) as energy pricing problem, in [Gilbert *et al.* \(2015\)](#); [Labbé & Violin \(2013\)](#); [Marcotte & Savard \(2002\)](#); [Robbins & Lunday \(2016\)](#) as pricing-setting problem, etc... As mentioned in [Gansterer & Hartl \(2017, 2018\)](#), among the literature studied CAs, BGP and WDP are studied separately, it seems there is no solution for the whole system (5-phase procedure for CAs) when we are facing a auction-based decentralized planning, the pricing strategies used in these two problems are either with a marginal price or a given pricing strategy as described in Section 2.3.1.2. Introducing bilevel structure between carriers/BGP and auctioneer/WDP allows us to adequately formulate their relationship, as the upper level/leader, carriers collaboratively or competitively choose their pricing strategies, knowing that the lower level/auctioneer is going to adapt his behavior - allocation bundle of lanes to carriers - accordingly.

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Chapter 3

The Winner Determination Problem in CAs

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3. THE WINNER DETERMINATION PROBLEM IN CAs

Auction can be used as a market protocol to allocate agent activities or resources in a multi-agent system. In Combinatorial Auctions (CAs), agents (bidders) bid on a subset of items (goods, tasks, resources, services, etc.), i.e. a bundle (Peter *et al.*, 2006). In CAs, bidders can express both their preference within bids for the items' complementarity * and substitutability † (Boughaci *et al.*, 2009). CAs has been widely used in economics, operation research, game theory and resource allocation in multi-agent systems (Boughaci & Drias, 2005; Collins *et al.*, 1999; Fujishima *et al.*, 1999; Leyton-Brown *et al.*, 2000b; Rothkopf *et al.*, 1998). Real-world applications can be found such as America's Federal Commissions (FCC) auctions ‡.

Under the context of CAs, one main issue is the Winner Determination Problem (WDP) (Lehmann *et al.*, 2006). The concept of WDP is expressed as follows: consider a set of bids in a CAs, find an item-conflict-free allocation to bidders (not all items need to be allocated) such that the auctioneer's revenue is maximized or the auctioneer's cost is minimized.

From a practical point of view, WDP has been used in the applications of multi-agent systems and other domains such as cloud computing (Samimi *et al.*, 2016; Tafsiri & Yousefi, 2018), e-commerce (De Vries & Vohra, 2003), intelligent transportation systems (De Vries & Vohra, 2003; Satunin & Babkin, 2014), services scheduling (Fontanini & Ferreira, 2014), knowledge management (Wu, 2001), logistics services (De Vries & Vohra, 2003; Ignatius *et al.*, 2011; Pla *et al.*, 2014) and production management (Ray *et al.*, 2011), etc.

WDP is reviewed under CAs in the paper De Vries & Vohra (2003), and this survey is devoted to the WDP which has never been individually reviewed. This chapter aims to depict how far WDP has been considered in different respects, and to better understand the current status of the research, and to branch the studies for the future. In this survey, our studies are focused on where operation research models are developed and solution techniques are applied.

*The value assigned to a collection of items should be greater than the sum of the values assigned to its individual's elements.

†The value assigned to a collection of items should be lower than the sum of the value attached to its individual's elements.

‡<http://wireless.fcc.gov/auctions/>.

The reminder of this chapter is organized as follows, Section 3.1 provides the general problem description as well as formulations for WDP. Details about the solution approach, the benchmarks and the computational study are given in Section 3.2, 3.3 and 3.4, respectively. Conclusions and further research are given in Section 3.6.

3.1 Problem formulation

Given $N = \{1, \dots, n\}$ the set of bidders and $M = \{1, \dots, m\}$ the set of items. A bundle S is a subset of items in M : $S \subseteq M$. Let $\mathcal{F}_i \subset M$ be the set of bundles for which bidder i submits an atomic bid, and $\mathcal{F} = \mathcal{F}_1 \cup \dots \mathcal{F}_n$ the set containing all the bundles demanded by at least one of the bidders. Each bidder i can give a bundle S an atomic bid $v_i(S)$ i.e., the highest price that bidder i is willing to pay for bundle S .

The items are allocated through variables $x_i(S) \in \{0, 1\}$: it equals to 1 when bidder i get bundle S . An allocation $(x_i(S)|i \in N, S \subseteq M)$ is said to be feasible if it allocates no item more than once:

$$\sum_{i \in N} \sum_{S \subseteq M, S \ni j} x_i(S) \leq 1 \quad \text{for all } j \in M, \quad (3.1)$$

and at most one bundle to every bidder

$$\sum_{S \subseteq M} x_i(S) \leq 1 \quad \text{for all } i \in N. \quad (3.2)$$

In Nisan & Ronen (1999), bidding languages are introduced to represent bids, through which bidders price the bundles with their own preferences, see also Nisan & Ronen (1999). *OR* and *XOR* bidding languages are widely used in this problem (see Chapter 2.2.3) and will be presented here, we give two refinements of *WDP*, called *WDP_{OR}* and *WDP_{XOP}* respectively. In both frameworks, bidders provide atomic bids for the bundles.

The *WDP* problem is defined as follows (De Vries & Vohra, 2003),

Definition 3.1 *Winner Determination Problem (WDP)*

Given bids $v_i(S), i = 1, \dots, n$ and $S \in \mathcal{F}$, the winner determination problem is the

3. THE WINNER DETERMINATION PROBLEM IN CAS

problem which determines

$$x \in \operatorname{argmax} \left(\sum_{i \in N} v_i(S) x_i(S) \mid x \text{ is a feasible allocation} \right). \quad (3.3)$$

In the **OR bidding language**, the atomic bids for bidder i can be seen as follows, i is willing to accept any combination of pairwise disjoint atomic bids a price equal to the summation of the disjoint bid prices. In this case, disjoint atomic bids can be combined as one bid, multiple bids can be given to one bidder as soon as it is feasible, constraint (3.2) is thus omitted, see Daniel *et al.* (2006).

Definition 3.2 (WDP_{OR})

Given a set of bids in the OR bidding language, with atomic bids on sets in \mathcal{F}_i for every bidder i , WDP_{OR} is the problem which computes

$$x \in \operatorname{argmax} \left(\sum_{i \in N} v_i(S) x_i(S) \mid x \text{ satisfies (3.1)} \right). \quad (3.4)$$

In **XOR bidding language**, the atomic bids for bidder i can be seen as follows, bidder i can only receive at most one atomic bid.

Definition 3.3 (WDP_{XOR})

Given a set of bids in the XOR bidding language, with atomic bids on sets in \mathcal{F}_i for every bidder i , WDP_{OR} is the problem which computes

$$x \in \operatorname{argmax} \left(\sum_{i \in N} v_i(S) x_i(S) \mid x \text{ satisfies (3.1) and (3.2)} \right). \quad (3.5)$$

3.1.1 General formulation of WDP

In most literature, problem WDP_{OR} is modeled as an integer linear program

$$\begin{aligned} \max \quad & \sum_{i=1}^n \sum_{S \subseteq M} v_i(S) x_i(S) \\ \text{subject to} \quad & \sum_{i \in N} \sum_{S \subseteq M, S \ni j} x_i(S) \leq 1 \quad \forall j \in M \\ & x_i(S) \in \{0, 1\} \quad \forall i \in N, S \subseteq M \end{aligned} \quad (3.6)$$

This model is identical to the integer linear programming model of the weighted set packing problem (Rothkopf *et al.*, 1998). In this problem, we consider a

collection of subsets (i.e. the bundle) of a set M , each subset with a weight (i.e. the valuation), and the goal is to find a non-intersecting sets of maximal total weight.

In problem WDP_{XOR} , extra constraints are added in (3.6):

$$\sum_{S \subseteq M} x_i(S) \leq 1 \quad \forall i \in N. \quad (3.7)$$

We can also model WDP_{OR} and WDP_{XOR} by using intersection graphs. Consider a finite un-directed graph $G = (U, E)$. The nodes in U are identical to the bids in \mathcal{F} , and an edge is build between two nodes if and only if there is a conflict between these two bids, i.e., there is an intersection between these two bids, or, in the case of WDP_{XOR} , both bids are by the same bidder. The node in $u \in U$ associated with the bid S are given a weight $w_i(u) := v_i(S)$. A subset of nodes in a graph is called a *stable set* if no two nodes are connected by an edge. The *maximum weighted stable set problem* is the problem to find a stable set of maximum total weight. WDP_{OR} and WDP_{XOR} can be seen as the maximum weighted stable set problem related to WDP_{OR} and WDP_{XOR} , respectively.

When we consider multi-unit supply or multiplicities of items in bids, [Holte \(2001\)](#) models WDP_{OR} and WDP_{XOR} as generalized knapsack problem.

3.1.2 Variants of WDP

3.1.2.1 Bi-objective WDP (2WDP-SC)

2WDP-SC is first introduced in [Buer & Pankratz \(2010b\)](#) as a generalization of set covering problem (SC). The goal of the problem is to find the best allocation such that the total cost is minimized, and total service quality is maximized.

Given $N = \{1, \dots, n\}$ the set of bidders, $M = \{1, \dots, m\}$ the set of items and \mathcal{F} the set of bundle bids, a bundle bid $S \in \mathcal{F}$ is defined as triple $S := (i, \tau, v_i(\tau))$, which implies that bidder $i \in N$ is willing to pay the subset τ at a price of $v_i(\tau)$. Given also the set $Q := \{q_{ij} | \forall i \in N \wedge j \in M\}$ where $q_{ij} \geq 0$ indicates the service quality level if bidder i fulfills j .

The goal is to find a non-intersection set of bids $W \subseteq \mathcal{F}$, such that every item in M is covered by W . Also, in the objective functions, the total cost f_1 need

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to be minimized and the total service quality f_2 needs to be maximized. The 2WDP-SC is modeled as follows (Buer & Pankratz, 2010b):

$$\begin{aligned}
 \min \quad & f_1(W) = \sum_{S \in W} v_i(S) \\
 \max \quad & f_2(W) = \sum_{j \in M} \max\{q_{ij} | i \in \{i(S) | S \in W \wedge i \in \tau(S)\}\} \\
 \text{subject to} \quad & \cup_{S \in W} \tau(S) = M
 \end{aligned} \tag{3.8}$$

In the paper of Asli *et al.* (2019), the authors propose a bi-objective winner determination problem, where the objectives are: (i) maximization of the total income, (ii) maximization of the number of sold items.

3.1.2.2 WDP under uncertainty (sWDP)

Uncertainty is one of the major tasks in most of the mathematical applications, to measure and to deal with the uncertainty is also part of WDP.

In the theoretical studies, in order to deal with the uncertainty, a min-max regret robust optimization approach is developed in Boutilier *et al.* (2004) to solve WDP under uncertainties within the auctioneer's objective function, also, a robust models is proposed in Sampath & Benyoucef (2009) to solve WDP with bid evaluation under uncertainty.

In the application of truckload (TL) procurement, Ma *et al.* (2010); Remli *et al.* (2019); Zhang *et al.* (2014, 2015) address WDP under shipment volume uncertainty. A two-stage stochastic WDP model is considered to differ from the classical WDP model. In this problem, the items are called lanes, a lane is defined as an origin-destination pair together with a volume of shipment needed to be transported from the origin to the destination, and the bidding price $v_i(S)$ is defined for one unit volume S by bidder i . The task is to minimize the total expected cost for the shipper (i.e, the auctioneer).

3.2 Methodology of the WDP problem

3.2.1 Complexity of WDP

In CAs, a set of items is traded simultaneously, and in the bidding process, bidders may bid for any combination of items. "The space of WDP problem is large, it has three degrees of freedom: the number of items, the number of bids and the distribution of bids" (Fujishima *et al.*, 1999). The solution of such auction is an optimization problem which is NP-hard in the general case (Rothkopf *et al.*, 1998). Sandholm *et al.* (2002) show how different features of a combinatorial market affect the complexity of determining the winners, and theoretically analyze the complexity of finding a feasible, approximate, or optimal solution.

Motivated by its potential applications and computation challenges, WDP has been studied and developed with a variety of optimization algorithms. Two classes of algorithms can be discovered in the literature, "exact" or "approximate". In general, exact algorithms can give the optimal solution and guarantee the optimality of the solution of all WDP instances. But in practice, on one hand, using exact algorithms to solve WDP requires exponential time, which makes them impractical with most real-world applications when the number of traded items grow (Dowlatshahi *et al.*, 2014); and on the other hand, approximate algorithms do not guarantee the optimality of the solutions, the optimality is sacrificed so that the problem could be solved more efficiently.

3.2.2 Exact algorithms for WDP

Applying exact algorithms to solve WDP can be tracked back to the beginning of 1970s (Padberg, 1973) when solving set packing problems. In Andersson *et al.* (2000); Caplice & Sheffi (2003), WDP is formulated as a standard mixed integer programming problem, see also Nisan & Ronen (1999); Wurman (1999), it enables the problem to be developed and solved by standard mixed integer programming algorithms.

3.2.2.1 Branch-and-bound (B&B)

A variety of work can be found to solve WDP is under the framework of branch-and-bound (B&B). These algorithms include the combinatorial auction structural

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search (CASS) (Fujishima *et al.*, 1999) which is based on the depth-first branch-&-bound algorithm, the linear programming based B&B algorithm (Nisan, 2000), the Combinatorial Auction Multi-Unit Search (CAMUS) (Leyton-Brown & Shoham, 2003; Leyton-Brown *et al.*, 2000b), the BOB algorithm (Sandholm & Suri, 2003), the CABOB algorithm (Sandholm *et al.*, 2005), and the clique-based B&B algorithm using graph coloring for bounding (Wu & Hao, 2016). In Wu & Hao (2016), an exact approach with an effective B&B algorithm is explored, Complete Set Partitioning problem captures the special case of WDP in CAs, where bidders place bids on every possible bundle of items. These B&B methods differ from each other mainly by

- specific techniques to determine the lower and upper bounds (Nisan, 2000; Sandholm & Suri, 2003; Sandholm *et al.*, 2005; Wu & Hao, 2016),
- their branching strategies (Fujishima *et al.*, 1999; Leyton-Brown *et al.*, 2000b; Wu & Hao, 2016),
- other techniques like preprocessing, decomposition of the bid graph, and identifying and solving tractable special cases (Sandholm & Suri, 2003; Sandholm *et al.*, 2005; Wu & Hao, 2016).

3.2.2.2 Branch-and-cut (B&C)

A set packing formulation for WDP studied within a branch-and-cut algorithm is given in Escudero *et al.* (2009). The authors study the polyhedral structure of the problem and propose a new and tighter formulation with some new valid inequalities.

3.2.2.3 Branch-and-price (B&P)

A branch-and-price algorithm is given in Günlük *et al.* (2005) also based on a set packing formulation proposed in Dietrich & Forrest (2001). B&P is said to be a powerful tool to combine column (or, variable) generation with enumeration to solve large integer programs.

3.2.2.4 Dynamic programming (DP)

Using DP to solve WDP is discussed in Rothkopf *et al.* (1998); Sandholm (2000). By using the optimal substructure property of the problem: the maximal revenue either from a single bid set or from two disjoint subsets of the same bid set, the dynamic programming explores the highest possible revenue of each bid set from the smallest to the largest.

The DP (Vangerven *et al.*, 2017) is proposed again for CAs with a specific geometric structure. In this restricted topology, every item corresponds to a rectangle with different size, and the items are arranged in rows.

3.2.3 Approximate algorithms for WDP

Approximate algorithms can be divided into three classes: approximation algorithms, problem-specific heuristics, and meta-heuristics (Dowlatshahi *et al.*, 2014). In general, approximation algorithms can obtain good quality solution within a run-time bounds; problem-specific heuristics are designed for a specific problem with particular objective functions or constraints, meta-heuristics provide more general approximate algorithms and are applicable to a large variety of optimization problems. "Meta-heuristics solve complex optimization problems by 'exploring' the large solution space and achieve this goal by effectively reducing the size of this space and 'exploiting' the reduced space efficiently" (Dowlatshahi *et al.*, 2014). Representative algorithms in this class includes Evolutionary Computation (EC), Ant Colony Optimization (ACO), Greedy Randomized Adaptive Search Procedure (GRASP), Tabu Search (TS), Variable Neighborhood Search (VNS), Iterated Local Search (ILS), Particle Swarm Optimization (PSO), Gravitational Search algorithm (GSA), etc.

3.2.3.1 Stochastic local search (SLS)

Casanova (Hoos & Boutilier, 2000) is a SLS algorithm that explores the space of the searching regions. Given a feasible allocation, Casanova adds an un-allocated bid and then removes the conflicting bids from the allocation at each iteration. The selection of the bids is based on the bids' quality and their history information.

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3.2.3.2 Limited discrepancy search (LDS)

Based on the idea of optimal algorithm IDA* in Sandholm (1999), Sakurai *et al.* (2001) introduce LDS techniques to limit the search efforts to the regions where good solutions are likely to exist.

3.2.3.3 Hybrid algorithm (HA)

A HA combining simulated annealing with branch-and-bound (SAGII) is proposed with three different local move operators: an embedded branch-and-bound move, greedy local search move, and exchange move (Guo *et al.*, 2006b).

In Dowlatshahi & Derhami (2017), a hybrid Ant Colony Optimization with a novel Multi-Neighborhood Local Search (ACO-MNLS) algorithm is proposed for solving WDP in CAs. MNLS uses the fact that the global optima of WDP is a local optima for a given neighborhood. The proposed MNLS algorithm simultaneously explores a set of three different neighborhoods to get different local optima and to escape from the deep local optima.

3.2.3.4 Tabu search (TS)

TS is a meta-heuristic algorithm to explore the searching space based on LS methods. A TS algorithm (Boughaci *et al.*, 2010), a crossover-based tabu search algorithm (TSX_WDP) (Sghir *et al.*, 2013) and a multi-neighborhood tabu search algorithm (MN/TS) (Wu & Hao, 2015) are proposed to solve WDP.

TSX_WDP is designed with two ways to generate complementary neighborhoods, called intensification and diversification. TSX_WDP also employs a backbone-based recombination operator to escape from the deep local optimal and to search into unexplored more promising regions.

MN/TS is a heuristic algorithm designed for maximum weight clique problem (MWCP) in Wu *et al.* (2012). In Wu & Hao (2015), WDP is transformed into the maximum weight clique problem.

3.2.3.5 Memetic algorithm (MA)

Boughaci *et al.* (2009) propose a MA for the optimal WDP, this algorithm is based on a SLS with a specific crossover operator. In every iteration of the LS, either a

random bid or a best bid is added with a probability p or $1 - p$ respectively, and the conflicting bids are removed in the allocation.

3.2.3.6 Greedy algorithm

[Lehmann *et al.* \(2002\)](#); [Zurel & Nisan \(2001\)](#) introduce a greedy algorithm, then [Fukuta & Ito \(2006\)](#) give a hill-climbing (HC) greedy algorithm and a SA-like random search algorithm in a more practical point of view.

3.2.3.7 Genetic algorithm (GA)

The GA method uses crossover and standard operators to increase the searching space without a local search (LS). In [Wang & Wang \(2014\)](#), a problem-specific mathematical model is designed to maximize the expected economization of a procurement, the GA method is used to solve the problem within the solution of WDP.

3.2.3.8 Lagrangian heuristic (LAHA)

The Lagrangian heuristic is introduced in [Beasley \(1990\)](#) to solve the set-covering problem. [Guo *et al.* \(2006a\)](#) model the CAs problem as a set packing and applied the Lagrangian relaxation method. [Hsieh \(2010\)](#) and [Mansouri & Hassini \(2015\)](#) solve the Lagrangian relaxation of WDP, the first one deals with multi-unit multi-item reverse WDP and the second one deals with the WDP in iterative CAs. In [Hsieh & Liao \(2014\)](#), an agent learning approach has been proposed for solving WDP, in which a Lagrangian relaxation approach is used to develop an efficient multi-agent learning algorithm.

3.2.3.9 Clique-based heuristic

WDP is said to be equivalent to the weight set packing problem ([De Vries & Vohra, 2003](#)), and in [Ausiello *et al.* \(1980\)](#), weight set packing problem is reduced as the maximum weight clique problem (MWCP). In [Guo *et al.* \(2006b\)](#), a clique-based branch-and-bound approach has been introduced for solving WDP, which is based on clique formulation of WDP, then it can be solved as the MWCP. [Wu & Hao \(2015\)](#) study the clique-based approach for WDP by applying a heuristic to the transformed MWCP problem.

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3.2.3.10 Ant Colony Optimization (ACO)

Using ant colony optimization to solve the WDP is started from the [Dowlatshahi & Derhami \(2017\)](#), the authors propose a hybrid Ant Colony Optimization with a novel Multi-Neighborhood Local Search (ACO-MNLS) algorithm. A Graph Based Ant Algorithm (TrACA) ([Ray *et al.*, 2018](#)) and an Ant Colony approach ([Ray & Ventresca, 2018](#)) are given one year later. In [Ray *et al.* \(2018\)](#), the IP formulation of the WDP problem is transformed into a graphical one where the set of bundles and associated bids are represented on a directed cyclic graph.

3.2.3.11 Other algorithms

[Dobzinski & Schapira \(2006\)](#) propose an improved approximation algorithms for CAs with submodular bidders. This class of bidders is also called *XOS* bidders.

In [Boughaci \(2010\)](#), a population-based metaheuristic, called differential evolution algorithm (DE) is studied for the WDP.

In [Nguyen \(2014\)](#), a new mathematical formulation for WDP (under the name of set packing) and an efficient method for generating near-optimal solution have been proposed.

In [Boughaci & Lassouaoui \(2014\)](#), a stochastic hyper-heuristic (SHH) for solving WDP has been proposed, in which a new idea is developed for hyper-heuristics by combining choice function and randomness strategies. In addition, to compare with the SHH algorithm, choice function (CF) and random (RHH) hyper-heuristics are also discussed.

3.2.4 Algorithms for 2WDP-SC

A multiobjective genetic algorithm ([Buer & Pankratz, 2010b](#)), a Pareto-based greedy randomized adaptive search procedure (GRASP) approach ([Buer & Pankratz, 2010a](#)), a Pareto-metaheuristic are proposed for solving the problem. In [Rekik & Mellouli \(2012\)](#), bidder's reputation is taken into account the decision making of the problem, to evaluate bidder reputations, the auctioneer uses a number of service attributes with different weights.

In [Buer & Kopfer \(2014\)](#), the authors have presented a metaheuristic approach by integrating the greedy randomized adaptive search procedure with a two-stage

candidate component selection procedure in order to find a competitive set of non-dominated solutions.

3.3 Benchmarks

In this section, we give some empirical test suites that were used in order to evaluate and compare the existing algorithms for WDP. It is generally agreed that no real-world benchmarks are available for WDP problem, here in this section, we provide the most used test suite created for WDP problem in the literature.

3.3.1 *Sandholm*

Sandholm is provided by [Sandholm \(1999\)](#), which can be used to generate instances of different problem sizes and distributions. There are four different distributions available: *Random*, *WeightedRandom*, *Uniform*, *Decay*, the *Decay* distribution in general leads to the hardest instance ([Sandholm, 2002](#)),

- *Random*: For each bid, pick the number of items randomly from $1, 2, \dots, m$. Randomly choose that many items without replacement. Pick the price randomly from $[0, 1]$.
- *WeightedRandom*: Same bid creation procedure, but pick the price between 0 and the number of items in the bid.
- *Uniform*: Randomly chosen items for each bid with same number. Pick the prices from $[0, 1]$.
- *Decay*: Give the bid with one random item. Then repeatedly add a new random item with probability α until an item is not added or the bid includes all m items. Pick the price between 0 and the number of items in the bid.

3.3.2 CATS

[Leyton-Brown et al. \(2000a\)](#) have created the program Combinatorial Auction Test Suite (CATS) to generate benchmarks. CATS is a suite of distributions

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which are parameterized by the number of items and bids. This suite of distributions models the realistic bidding behavior, it provides an economic motivation for both the contents and the valuation of a bundle, deriving them from basic bidder preferences.

Different distributions are available in the CATS suite: *paths*, *regions*, *matching*, *scheduling*, and *arbitrary*,

- *paths*: Bids are build in space - an actual map, it begins generate *num-cities* nodes randomly placed on a plane. then, iteratively consider random pairs of nodes and examine the shortest path connecting them, each path is treated as a bid with a price, the price is random in (parameterized) proportion to the Euclidean distance between the chosen nodes.
- *regions*: Bids are build in adjacency graph, the items are adjacency connected in the graph with different common values and private values for each bidder (the value combination is used to show bidders' preferences). To generate the bids, it first add a random item, weighted by a bidder's preferences, to the bidder's bid; next, determine whether another item should be added by drawing a value uniformly from $[0,1]$, and adding another item if this value is smaller than a threshold, in this procedure, it allows a small chance that a new item will be added uniformly at random from the set of items, without the requirement that it be adjacent to a item in the current bundle S , otherwise, select a item from the set of nodes bordering the items in S . The probability that some adjacent item n will be added depends on how many edges n shares with the current bundle S , and on the bidder's relative private valuations for n , the price for each bid depends on the sum of common and private valuations for the items in the bundle; finally, additional bids that are substitutable for the original bid are generated, with the constraint that each new bid contains at least one item from the original bid.
- *matching*: Bids are build based on matching problems, in which corresponding time slices must be secured on multiple resources. The general form of temporal matching includes m sets of resources, in which each bidder wants 1 time slice from each of $j \leq m$ sets subject to certain constraints on how the times may relate to one another. The bids are generated based on the

time deviation of the defined matching problem, and the price of a bid is derived from a particular bidder’s utility function.

- *scheduling*: Bids are build based on job-shop scheduling problems. First, determine the number of deadlines for a given job according to a decay distribution, and then generate a set of substitutable bids satisfying the deadline constraints. Specifically, let the set of deadlines of a particular job be $d_1 < \dots < d_n$ and the value of a job completed by d_1 be v_1 , superadditive in the job length. The price of a job completed by deadline d_i is $v_i = v_1 \frac{d_1}{d_i}$, reflecting the intuition that the decrease in value for a later deadline is proportional to its ‘lateness’.
- *arbitrary*: Bid are build with arbitrary relationship in a fully-connected graph, it express the likelihood that a particular pair of items will appear together in a bundle. To generate the bids, it choose a first item and then proceed to add items one by one, with the probability the new item shared with the current bundle.

More information on the test suite can be found at <http://robotics.stanford.edu/CATS>.

3.3.3 REL

Lau & Goh (2002) provide new benchmarks of various sizes consisting of up to 1500 items and 1500 bids. These benchmarks include 500 instances. These instances are considered in Lau & Goh (2002) as more realistic than other instances and are divided into 5 different groups, each group having 100 instances labeled as *REL* – $m - n$, where m is the number of item and n is the number of bid. To generate these instances, several factors are incorporated, including a pricing factor which models a bidder’s acceptable price range for each bid, a preference factor which takes into account bidder’s preferences among bids, and a fairness factor which measures the fairness in distributing items among bidders.

3.3.4 Complementary data

Fujishima *et al.* (1999) (*Fuji* sets) provide two more distributions to generate instances: *binomial* and *exponential*, and De Vries & Vohra (2003) (*deVries* sets)

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provide the distribution *quadratic*, they use distribution functions to determine how often a bid for n items appears, the probability of each item being included in a given bid is independent of which other items are included.

Aside from the general setting WDP problem, in [Günlük *et al.* \(2005\)](#), in order to generate multi-round bids using XOR-of-OR language, the authors construct problem instances from the round-by-round results of FCC auction. While [Guo *et al.* \(2006a\)](#) propose a new methodology to produce the Proportional Bid Price(*PBP*) SPP test set.

3.4 Performance of the algorithms

The performance of the proposed algorithms are evaluated in terms of solution quality and computation time by several well-known benchmarks. Since there is no real-world benchmarks are available, thus identifying what types distributions can be solved more efficiently by what types algorithms is rather important. In the following section, only the algorithms that are based on the nature formulation of WDP are considered and they are listed by the year of publication, the algorithms that devoted to specific case WDP will not be taken into account the consideration.

3.4.1 Exact algorithms

CASS ([Fujishima *et al.*, 1999](#)) demonstrates excellent performance both in finding optimal allocations and as an anytime algorithm. CASS's effectiveness is strongly influenced by the distribution (*Binomial*, *Exponential*) of bids, especially when the number of items increases. CASS is compared with IDA*, it outperforms IDA* ([Sandholm, 1999](#)) for the search strategy and the preprocessing - two orders of magnitude faster.

CPLEX (MIP) ([Andersson *et al.*, 2000](#)) (version 6.5) performs well comparing with IDA* ([Sandholm, 1999](#)) for all the distributions (*Random*, *WeightedRandom*, *Uniform*, *Decay*) introduced in [Sandholm \(1999\)](#) - five orders of magnitude faster, and CASS is faster than CPLEX for some distributions (*Binomial*, *Exponential*) introduced in [Fujishima *et al.* \(1999\)](#).

CAMUS ([Leyton-Brown *et al.*, 2000b](#)) is targeted for multi-unit combinatorial auction, it is the generalization and extension of CASS algorithm. CAMUS

3.4 Performance of the algorithms

introduce the B&B technique for computing upper bounds on the optimal outcome. The algorithm is tested on *Random* distribution. CAMUS’s performance is sub-exponential in the number of items and as an anytime algorithm, it can find a 99% optimal solution an order of magnitude more quickly than it finish the complete run, which suggests that CAMUS could be useful on large problems.

CABOB (Sandholm *et al.*, 2005) uses decomposition techniques, upper and lower bounding, elaborate and dynamically choose bid-ordering heuristics. It is compared with CPLEX (version 8.0, the fastest optimal algorithm by the time), CPLEX uses best-bound search which requires exponential search, while CABOB uses depth-first branch-and-bound (DFBnB), which runs in linear space. The algorithm together with CPLEX are tested on the *Sandholm* and *CATS* distribution, CABOB has better anytime performance than CPLEX and can achieve close to optimal solution quality faster than CPLEX.

B&P (Günlük *et al.*, 2005) uses XOR-of-OR (the combination of XOR and OR bidding language) bidding for FCC-auction. It is tested on the distribution of *Sandholm*, *Fuji* and *deVries*. The algorithm manages to solve almost all these instances within 10 minutes and performs better than the natural formulation solved using CPLEX in the case that the columns in the column generation can be generated and the formulation is stronger.

B&C (Escudero *et al.*, 2009) algorithm offers a tighter formulation based on the polyhedral structure of the set packing formulation and introduces several techniques in the data preprocessing and some useful inequalities. The test is done in comparison with CPLEX version 9.1 on *CATS* distribution. B&C is faster than CPLEX for the hard instances (the hardest instances can be solved in two minutes while CPLEX took almost one hour), and it can reduce the duality gap significantly.

MaxWClique (Wu & Hao, 2016) introduces some specific bounding and branching strategies, and it is tested on *Sandholm*, *CATS*, and *REL* distributions compared with CPLEX version 12.4. *MaxWClique* outperforms CPLEX 12.4 solver on the whole set of the *REL* instance; For *Sandholm* instances, *MaxWClique* is slightly faster for *Random* distribution, but significantly better for *Uniform* distribution, and *Decay* distribution is significantly hard for *MaxWClique*; For *CATS* distribution, CPLEX performs much better and much faster than *MaxWClique*.

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Table 3.1: Exact algorithms for WDP

References	Algorithm	Test suits	Performance
(Sandholm, 1999)	IDA*	<i>Sandholm</i>	
(Fujishima <i>et al.</i> , 1999)	CASS	<i>Fuji</i>	Outperform <i>Sandholm</i> 's algorithm
(Andersson <i>et al.</i> , 2000)	CPLEX	<i>Fuji</i> , <i>Sandholm</i>	Faster than CASS
(Leyton-Brown <i>et al.</i> , 2000b)	CAMUS	CATS	Useful for large problem
(Sandholm & Suri, 2003)	BOB	No experimental	
(Sandholm <i>et al.</i> , 2005)	CABOB	<i>Sandholm</i> , CATS	Outperform CPLEX for most sets CATS
(Günlük <i>et al.</i> , 2005)	B&P	FCC	Faster than CPLEX
(Escudero <i>et al.</i> , 2009)	B&C	CATS	Outperform CPLEX
(Wu & Hao, 2016)	<i>MaxWClique</i>	<i>Sandholm</i> , CATS, <i>REL</i>	Outperform CPLEX for sets <i>REL</i>
(Vangerven <i>et al.</i> , 2017)	DP	No experimental	

In conclusion, the presented exact algorithms may be useful on certain distributions but using CPLEX solver seems still powerful facing the nature formulation of the WDP, see Andersson *et al.* (2000); Günlük *et al.* (2005); Guo *et al.* (2006b); Sandholm *et al.* (2005); Wu & Hao (2016).

3.4.2 Approximate algorithms

Casanova (Hoos & Boutilier, 2000) is tested on several random problem distributions, and its performance is compared with CASS. High quality solutions are found by Casanova much faster than CASS, Casanova outperforms CASS on large problem instances; and on small instances, though incomplete.

SAGII (Guo *et al.*, 2006a) together with CPLEX and Casanova are compared and tested with CATS for different distributions and *REL* distribution. The experimental results show SAGII outperforms significantly Casanova and the CPLEX 8.0 solver for *REL* instances.

LAHA (Lagrangian) heuristic (Guo *et al.*, 2006a) uses 8 different distributions generated from CATS, namely the *exponential*, *random*, *uniform*, *binomial*, *decay*, *scheduling*, *matching* and *paths* distributions and the *PBP* distribution. LAHA provides high quality results for all CATS tests suite, it obtains optimal solutions for both *exponential*, *random*, *binomial* and *scheduling* distributions. For the rest, it obtains the solution within 1% of optimal. While for *PBP* test set, LAHA performs at least as same as CPLEX in less CPU time.

HC-all and **SA** (Fukuta & Ito, 2006) use the *Random* distribution and conduct a detailed comparison to the **Greedy approach** introduced in Zurel & Nisan (2001), it shows that HC-all and SA are slightly better in optimality (0.997). The algorithms are also demonstrated as anytime algorithm that can be applied to large and dynamic problems.

3.4 Performance of the algorithms

MA algorithm (Boughaci *et al.*, 2009) is tested on the *REL* distributions and does the comparison with GA, SAGII and Casanova. The results show that MA can find better solutions than GA in less CPU time. MA performs better than Casanova (29-44% improvement) with less CPU time on all checked instances. The SAGII and MA all perform well with respect to certain distributions. In general, MA is a powerful tool to solve realistic instances.

SLS and **TS** algorithms (Boughaci *et al.*, 2010) are tested on the *REL* distributions and compared with Casanova, SAGII and MA. In general, SLS and TS can obtain qualified solutions for all benchmarks efficiently, the combination between diversification and intensification plays a key role to effectively find the good solutions. It shows that the result from SAGII has the 28% to 42% improvement in comparison to Casanova within less CPU time. As for SAGII and MA, they provides similar results.

DE (Boughaci, 2010) algorithm is tested on the *REL* distribution and compared to the methods including SAGII, GA, and MA. SAGII, MA and DE show a good performance all checked benchmarks, and outperform GA in both solution quality and efficiency. Only for certain instances (*REL*-500-1000 and *REL*1000-1000 instances), DE performs better than SAGII and MA.

TSX_WDP (Sghir *et al.*, 2013) is tested on the *REL* distributions and compared with five algorithms from the above: Casanova, SAGII, SLS, TS, MA. TSX_WDP gives an improvement between 31% and 47% in solution quality compared to Casanova, between 4% and 8% compared to SLS, between 4% and 9% compared with TS, between 2% and 7% compared to MA, between 1% and 7% compared to SAGII.

SHH (Boughaci & Lassouaoui, 2014) is tested on *REL* distribution and compared with **CF**, **RHH** and **SLS**. The experimental results show that the stochastic SHH succeed to find good results for all the benchmark problems. They always outperform CF and RHH in both solution quality and efficiency. SHH performs also better than SLS on all the tested instances, it finds better solutions in shorter CPU time.

MN/TS (Wu & Hao, 2015) is tested on CATS, Sandhlo and *REL* distribution and compared with CPLEX version 12.4 and MA. For *REL* distribution, the results show that MN/TS dominates MA both in terms of solution quality and computing time and performs better than CPLEX 12.4 solver for most of the

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instances and very stable, and it outperforms SAGII, Casanova. For *Sandhlom* distributions, MN/TS outperforms CPLEX by producing much better results in solution quality on *Random*, *Uniform* distribution, but worse than CPLEX both in terms of solution quality and computing time on *Decay* distribution. For CATS distribution, CPLEX performs better than MN/TS for all tested instances both on the solution quality and computing time.

ACO-MNLS (Dowlatshahi & Derhami, 2017) is compared with four different metaheuristics for solving WDP, i.e. SLS, TS, GA, MA for solving *REL* distribution. The experimental results of ACO-MNLS show that ACO-MNLS outperforms the current best performing WDP metaheuristics in both the solution quality and computational efficiency.

TrACA (Ray *et al.*, 2018) is compared with MA and CPLEX for solving *REL* distribution. Results indicate that in a given run-time, the median of results from TrACA statistically significantly outperforms MA results in 85 percents of the cases. Further, the best value from TrACA is at least as good as MA values in 100 percents of the cases.

For conclusion, the proposed approximate algorithms could be all useful for certain distributions and they complement each other in the study. To the best of our knowledge, ACO-MNLS has the best results, it outperforms the GA, MA, SLS and TS algorithms in terms of the computational time, and overcomes the GA, TS, MA and SLS algorithms in terms of the solution quality in most problems, whereas in the case of other problems, both ACO-MNLS and other algorithms get the same results.

3.5 Investigated papers

Papers selected are positioned according to 4 criteria of classification: the article's methodology, the bidding language, the method type and the algorithm.

5 categories of methodology can be observed. (a) Conceptual analysis that is the theoretical studies which report issues and challenges, or give definitions without any numerical or empirical studies, (b) case study in which data from practitioners are used to test and analyze the results, (c) literature review that is an evaluative report of information found in the literature which is related to

Table 3.2: Approximated algorithms for WDP

References	Algorithm	Test suits	Performance
(Hoos & Boutilier, 2000)	Casanova (SLS)	<i>Fuji</i>	Outperform CASS for large instances
(Sakurai <i>et al.</i> , 2001)	LDS	<i>Sandholm, Fuji</i>	No comparison
(Zurel & Nisan, 2001)	Greedy	<i>Sandholm</i>	No comparison
(Lehmann <i>et al.</i> , 2002)	Greedy	No experimental	
(Guo <i>et al.</i> , 2006a)	LAHA heuristic	CATS, PBP	Ourperform CPLEX for sets <i>PBP</i>
(Guo <i>et al.</i> , 2006b)	SAGII	CATS, <i>REL</i>	Outperform Casanova and CPLEX
(Fukuta & Ito, 2006)	HC-all, SA	<i>Uniform</i>	Better than GA for optimality
(Dobzinski & Schapira, 2006)		No experimental	
(Boughaci <i>et al.</i> , 2009)	MA	<i>REL</i>	Outperform Genetic, Casanova
(Boughaci <i>et al.</i> , 2010)	SLS, TS	<i>REL</i>	SLS outperforms Casanova and TS
(Boughaci, 2010)	DE	<i>REL</i>	Outperform GA
(Hsieh, 2010)	LR	No experimental	
(Lavi & Swamy, 2011)		No experimental	
(Sghir <i>et al.</i> , 2013)	TSX_WDP	<i>REL</i>	Outperform Casanova, SLS, TS, MA, SAGII
(Boughaci & Lassouaoui, 2014)	SHH, CF, RHH	<i>REL</i>	Outperform SLS
(Hsieh & Liao, 2014)	Agent learning approach	No details	
(Wu & Hao, 2015)	MN/TS	CATS, <i>REL</i> , <i>Sandholm</i>	Outperform Casanova, MA, SAGII for sets <i>REL</i>
(Mansouri & Hassini, 2015)	LR	CATS	
(Dowlatshahi & Derhami, 2017)	ACO-MNLS	<i>REL</i>	Outperform SLS, TS, GA, MA
(Ray <i>et al.</i> , 2018)	TrACA	CATS, <i>REL</i>	Outperform MA
(Ray & Ventresca, 2018)	ACO	CATS, <i>REL</i>	Outperform MA

Table 3.3: Literature review of conceptual analysis for WDP

References	Methodology	Bidding language	Method	Algorithm
(Abrache <i>et al.</i> , 2007)	Conceptual analysis			
(Caplice & Sheffi, 2003)	Conceptual analysis	OR		
(Caplice & Sheffi, 2006)	Conceptual analysis			
(Cerquides <i>et al.</i> , 2007)	Conceptual analysis			
(Daniel <i>et al.</i> , 2006)	Conceptual analysis			
(De Vries & Vohra, 2003)	Literature review			
(Gujo, 2008)	Conceptual analysis			
(Lavi & Swamy, 2011)	Conceptual analysis			
(Lehmann <i>et al.</i> , 2006)	Conceptual analysis	OR, XOR		
(Lehmann <i>et al.</i> , 2002)	Conceptual analysis			
(Leyton-Brown <i>et al.</i> , 2000a)	Conceptual analysis			
(Nisan, 2000)	Conceptual analysis			
(Nisan & Ronen, 1999)	Conceptual analysis			
(Parkes & Ungar, 2000)	Conceptual analysis			
(Peter <i>et al.</i> , 2006)	Conceptual analysis			
(Ray <i>et al.</i> , 2011)	Conceptual analysis			
(Rothkopf <i>et al.</i> , 1998)	Conceptual analysis			
(Sandholm, 2000)	Conceptual analysis	XOR		
(Sandholm <i>et al.</i> , 2002)	Conceptual analysis	XOR	Exact	IDA
(Sheffi, 2004b)	Conceptual analysis			

a specific area of study, (d) empirical study that is based on observed and measured phenomena and derives knowledge from actual experience rather than from theory or belief and (e) numerical experiment that is the study of approximation techniques for solving a problem, taking into account the extent of possible errors.

The first part is classified as conceptual analysis that as in Table 3.3. Table 3.4 is classified as numerical and empirical study.

3.6 Conclusions

In this Chapter, a detailed survey about WDP is given to summarized the general and variants of the formulations for WDP. The complexity of the problem is

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Table 3.4: Literature review of numerical and empirical study for WDP

References	Methodology	Bidding language	Method	Algorithm
(Amor <i>et al.</i> , 2016)	Empirical study	XOR	Stochastic	Monte Carlo approach
(Andersson <i>et al.</i> , 2000)	Empirical study	OR	Exact	Mixed integer programming
(Asli <i>et al.</i> , 2019)	Empirical study	OR	Heuristic	Fuzzy
(Boughaci <i>et al.</i> , 2009)	Numerical experiments	OR	Heuristic	Memetic algorithm (SLS)
(Boughaci <i>et al.</i> , 2010)	Numerical experiments	OR	Heuristic	Equilibrium-based LS
(Boughaci, 2010)	Numerical experiments	OR	Heuristic	DE
(Boughaci, 2013)	Numerical experiments	OR	Heuristic	
(Boughaci & Lassouaoui, 2014)	Numerical experiments	OR	Heuristic	SHH
(Boutilier <i>et al.</i> , 2004)	Empirical study	OR	Robust	Min-max regret
(Buer & Pankratz, 2010a)	Numerical experiments	OR	Heuristic	Pareto-based GRASP
(Buer & Pankratz, 2010b)	Numerical experiments	OR	Exact, Heuristic	B&B, genetic algorithm
(Buer & Kopfer, 2011)	Numerical experiments	OR	Heuristic	HPNS
(Buer & Kopfer, 2014)	Numerical experiments	OR	Heuristic	Pareto-metaheuristic
(Dowlatshahi & Derhami, 2017)	Numerical experiments	OR	Heuristic	Hybrid ACO, MNLS
(Chen <i>et al.</i> , 2009)	Empirical study	OR	Heuristic	Implicit bidding approach
(Cohn <i>et al.</i> , 2008)	Empirical study		Heuristic	Implicit bidding approach
(Dobzinski & Schapira, 2006)	Numerical experiment		Heuristic	$e/e-1$ approximation
(Escudero <i>et al.</i> , 2009)	Numerical experiment	XOR	Exact	B&C algorithm
(Fujishima <i>et al.</i> , 1999)	Numerical experiment		Exact, Heuristic	CASS, VSA
(Fukuta & Ito, 2006)	Numerical experiment		Heuristic	Greedy algorithm
(Günlük <i>et al.</i> , 2005)	Numerical experiment	XOR-of-OR	Exact	B&P
(Guo <i>et al.</i> , 2003)	Numerical experiment		Heuristic	GA+TS
(Guo <i>et al.</i> , 2006a)	Numerical experiment	OR	Heuristic	Lagrangian relaxation
(Guo <i>et al.</i> , 2006b)	Numerical experiment	OR	Heuristic	Hybrid algorithm
(Hoos & Boutilier, 2000)	Numerical experiment		Heuristic	SLS
(Holte, 2001)	Numerical experiment		Heuristic	HCA
(Hsieh, 2010)	Numerical experiment	OR	Heuristic	Lagrangian relaxation
(Hsieh & Liao, 2014)	Numerical experiment	OR	Heuristic	Lagrangian relaxation
(Lau & Goh, 2002)	Case study		Heuristic	GA + LS
(Leyton-Brown <i>et al.</i> , 2000b)	Empirical study	OR	Exact	CAMUS
(Ma <i>et al.</i> , 2010)	Empirical study	OR		Stochastic programming
(Mansouri & Hassini, 2015)	Numerical experiment	OR	Heuristic	Lagrangian relaxation
(Mansouri & Hassini, 2019)	Empirical study	OR	Heuristic	Lagrangian relaxation
(Michalak <i>et al.</i> , 2016)	Numerical experiment		Heuristic	ODP-IP
(Mito & Fujita, 2004)	Numerical experiment		Heuristic	Greedy algorithm
(Nguyen, 2014)	Empirical study		Heuristic	Constraint generation
(Othmane <i>et al.</i> , 2014b)	Empirical study	OR		
(Ray <i>et al.</i> , 2018)	Numerical experiment	XOR	Heuristic	TrACA
(Ray & Ventresca, 2018)	Numerical experiment	XOR	Heuristic	ACO
(Rekik & Mellouli, 2012)	Empirical study	XOR		
(Remli & Rekik, 2013)	Empirical study	XOR	Robust	Constraint Generation
(Remli <i>et al.</i> , 2019)	Empirical study	XOR	Robust	Constraint Generation
(Sakurai <i>et al.</i> , 2001)	Numerical experiment	XOR	Heuristic	LDS
(Sandholm, 1999)	Numerical experiment	OR	Exact	IDA
(Sandholm & Suri, 2003)	Numerical experiment	XOR	Exact	BOB
(Sandholm <i>et al.</i> , 2002)	Empirical study	XOR	Exact	Mixed integer programming
(Sandholm <i>et al.</i> , 2005)	Numerical experiment	XOR	Exact	Cabob
(Schwind <i>et al.</i> , 2003)	Numerical experiment	OR	Heuristic	SG, SA, GA
(Sghir <i>et al.</i> , 2013)	Numerical experiment	OR	Heuristic	Tabu search
(Tsung <i>et al.</i> , 2011)	Numerical experiment		Heuristic	NESA
(Vangerven <i>et al.</i> , 2017)	Empirical study		Exact	Dynamic Programming
(van Norden <i>et al.</i> , 2006)	Empirical study		Exact, heuristic	ILP, fast randomized heuristic
(Wang & Wang, 2014)	Case study		Heuristic	GA
(Wu & Hao, 2015)	Numerical experiment	OR	Heuristic	Tabu search
(Wu & Hao, 2016)	Numerical experiment	OR	Exact	Clique-based B&B
(Zhang <i>et al.</i> , 2014)	Empirical study	OR	Stochastic	Monte Carlo approach
(Zhang <i>et al.</i> , 2015)	Empirical study	OR	Robust	Data-driven approach
(Zurel & Nisan, 2001)	Numerical experiment	OR	Heuristic	Greedy algorithm

analyzed. We investigate the exact and approximated algorithms that are used in solving WDP accurately and efficiently. The most used benchmarks are classified and the performance of the algorithms is compared.

From the reviewed methods, we observe that, although exact methods have the theoretical advantages to find the optimal solution, their computation time generally grows exponentially with the problem size, and this makes them less attractive for solving large size problems or real-world applications. On the other hand, heuristic algorithms can solve WDP with polynomial time complexity, but they are less efficient and less effective.

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Chapter 4

Bundle Construction Problem in CAs for Full Truckload Transportation Procurement

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4. BUNDLE CONSTRUCTION PROBLEM IN CAS FOR FULL TRUCKLOAD TRANSPORTATION PROCUREMENT

Over the past two decades, combinatorial auctions (CAs) (Peter *et al.*, 2006) has attracted more and more attentions both in theoretical and practical studies. The advantage of CAs is that the bidders can fully express their preferences when items are complements and substitutes due to the economies of scope and economies of scale. In conclusion, with CAs, the bidders can generate more profit or save more cost.

In a competitive transportation procurement system, due to the synergies available on the transportation pathways (Triki, 2016; Wang & Wang, 2015; Xu & Huang, 2014a,b), CAs allows carriers to bid on combinations of lanes as a packages instead of bidding only on individual lane, in which, carriers can express their preferences when they group transportation lanes into packages (Sheffi, 2004a; Triki *et al.*, 2014). In other words, combining multiple lanes as a tour or a continuous move by carriers allows them to decrease their empty mileage and thereby reduce cost (Chen *et al.*, 2009) or to generate greater profits (Chang, 2009; Jothi Basu *et al.*, 2015).

In transportation procurement, CAs generally follows a 5-phase procedure (Berger & Bierwirth, 2010):

- Carriers determine request lanes and put them into the auction pool;
- Bid Generation Problem (BGP): Auctioneer (Shipper or Third-party logistics - 3PL) generates bundles of requests and sends them to the carriers;
- Bid Generation Problem (BGP): Carriers give their bids for the offered bundles;
- Winner Determination Problem (WDP): Auctioneer allocates bundles to carriers based on their bids;
- Gained profits are distributed among the carriers.

In this thesis, we mainly focus on the second phase of the procurement. To address this problem, we assume a market place representing shippers who uses CAs to allocate lanes to carriers. A request lane is defined as a pick-up/delivery location pair with time constraints. And we focus only the full truckload transportation for study, not only because of its economical importance as shown in 1.2, but also because it is easier to implement and can be easily extended to less

than truckload case. The problem of defining feasible bundles is a problem of route-building or route-construction as introduced in [Baker & Schaffer \(1986\)](#) as VRPTW (vehicle routing problem with time windows). Although VRPTW is developed to minimize the total route cost or total tour time for a given task, the problem addressed in this thesis is to maximize the profit for carriers. We study the Bundle Construction Problem (BCP) under CAs specially for full truckload transportation procurement. More precisely, for a given set of carriers, we generate - find and select - feasible bundles with high quality respecting the carriers' flexibility and time budget.

In BCP, not all lane requests need to be visited. Indeed, the carriers only have to determine all the bundles that they can handle which generates profit. This problem is also recognized as an Orienteering Problem with Time Windows (OPTW). The OPTW problem is a route-construction problem in which a subset of requests are determined to visit, such that the total profit/score are maximized and the time constraints is not exceeded ([Gunawan *et al.*, 2016](#)). [Righini & Salani \(2006, 2008\)](#) develop bounded bi-directional dynamic programming to solve the elementary shortest path problems with additional resource constraints, and [Righini & Salani \(2009\)](#) apply it to solve the OPTW. The idea is to build paths from both the origin and the destination and match forward and backward paths to yield complete solutions.

The remainder of this chapter is organized as follows: Section 1 gives a scientific literature review. Section 2 defines the problem under study. In Section 3, we establish a mixed integer formulation of the problem to determine how the optimal bundles can be given. Section 4 proposes the dynamic programming algorithm to solve the proposed model. Numerical results are commented in Section 5. Section 6 summarizes the main findings and suggests extensions.

4.1 Literature review

As mentioned above, in BGP, auctioneer generates bundles of requests and sends them to the carriers. And BCP considered as part of BGP, the conceptual analysis is polarized. As in the 5-phase procedure for CAs-based transportation procurement ([Berger & Bierwirth, 2010](#)), with request lanes contained in the auction

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pool, the auctioneer in Phase 2 needs to determine attractive bundling of requests such that the carriers are more incentive to bid in Phase 3. Under this setting, each carrier can theoretically submit up to $2^n - 1$ different combinations of bundles to the auctioneer, where n is the number of requests that are traded. This is not manageable for realistic applications. Moreover, due to inaccurate information and different methodologies from the carriers, only a small subset of the useful combinations is actually found in practice even for large networks (Caplice & Sheffi, 2003). Alternatively, the BCP in Phase 2 can be determined by carriers themselves. As mentioned in Caplice & Sheffi (2003); Crainic & Gendreau (2002), carriers can combine their personal information - truck capacity, time budget, existing network etc. - with the complex market information to determine the most profitable bundles and bid strategies. Chang *et al.* (2002); Crainic & Gendreau (2003) have proposed efficient tools to assist the carriers to determine the best bundle selection. Moreover, Caplice & Sheffi (2003) propose a collaborative approach for both shippers and carriers to secure and manage their strategic relationship and to yield better solution.

Most of the research in this domain is focused on explicit computation of bundle bids for truckload transportation auctions. Song & Regan (2003a) present the first carrier model based on optimization approximation to determine the useful bundles. Wang & Xia (2005) clarify the bidder's optimality criterion in a combinatorial bid and studied a bundling method. Lee *et al.* (2007) develop a utility maximization decision problem in which the carriers determine the best packages to bid for in CAs and presented a column generation approach to solve the underlying nonlinear quadratic integer program. Chang (2009) develop a bidding advisor to assist truckload carriers in overcoming the challenges in the one-shot CAs. Chen *et al.* (2009) describe an approach to CAs for truckload procurement allowing to implicitly determine the complete set of all possible bids without of an exponential number of bids on either the bidders or the auctioneer. They provide also extensive computational results to demonstrate the tractability of the proposed approach. Ueasangkomsate & Lohatepanont (2012) introduce a bidding strategy for carriers facing a hard valuation problem on all possible routes. Triki *et al.* (2014) focus on the generation of load bundles to be submitted by carriers participating in CAs for long-haul full truckload transportation services and develop a probabilistic optimization model integrating the bid generation and

pricing problems jointly with the carriers fleet routing. Two heuristic procedures are proposed to solve instances with up to 400 auctioned loads. [Kuyzu *et al.* \(2015\)](#) formulate a stochastic bid price optimization model to maximize the carriers expected profit which accounted for lane synergies and competing carriers bid patterns. An iterative coordinate search algorithm is then developed to find high quality solutions. [Triki \(2016\)](#) develop an optimization approach based on the use of the location techniques by maximizing the synergy among the bundle's auctioned loads from one side and between the auctioned and the preexisting loads from the other side.

However, only a few papers address the less than full truckload freight transportation problems. [Mesa-Arango & Ukkusuri \(2013\)](#) investigate the benefits and provide some insights into the competitiveness and challenges associated with the development of consolidated bids (suitable for less than truckload operations). These lost one are constructed using a multicommodity one-to-one pickup and delivery vehicle routing problem solved through a branch-and-price algorithm. [Gansterer & Hartl \(2018\)](#) investigate a carrier collaborative BGP which allows carriers to exchange requests. They develop a proxy for the objective function to assess the attractiveness of bundles under incomplete information. A genetic-based algorithms is defined to generate attractive and feasible bundles. In [Yan *et al.* \(2018\)](#), a mixed integer programming method is developed to generate the best bid of the carriers using a bundled price to maximize their utility and increase the chance of winning the business.

4.2 Problem statement

In BCP, three types of carriers are considered:

- traditional carriers. They have no information about the bids. They prefer to bid on the bundles defining as a tour where a vehicle leave/return at the same location;
- informed carriers. They have part information about their future bids, i.e. they know part of their tasks (including lanes and their resources). They bid on the bundles that can be included in their current routing plan to gain the cost reduction;

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- spot market. It covers all the requests not taken by above two carriers.

In other words, traditional carriers can be seen as the freight transport companies; informed carriers can be seen as the industrial producers sharing transportation services during their own transportation tasks e.g. adding new lanes in their current network. For example, after serving its own customer, instead of returning back with an empty truck to the origin, a producer can offer transportation capacity for other delivery tasks respecting his own time constraints to go back. However, all type carriers can be seen as the informed carrier when given a specific setting.

Hereafter, each lane is defined with a origin-destination with time windows, we refer it as a lane request. The key goal to is to construct the feasible bundles and select the bundle sets with high quality for each carrier, which is the BCP defined at the beginning of this chapter.

To precisely define the feasible request bundles in transportation procurement, the following rules and assumptions are considered:

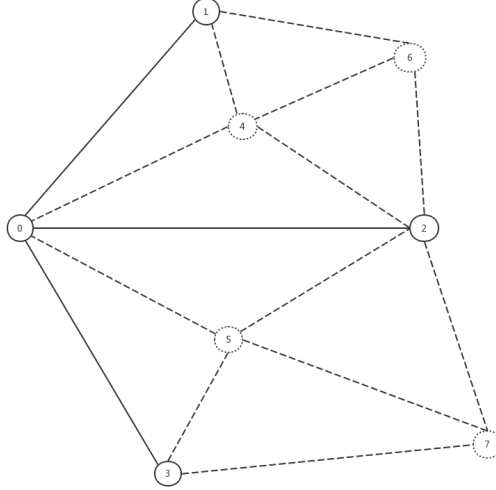
- the request bundles need to satisfy two conditions: "route compatibility and carrier's capacity" (Lafkihi *et al.*, 2017). More precisely, a carrier must be able to accomplish his shipping task. Thus, only the requests along the same route and within the carrier's limited capacity (residual volume, number of trucks, etc.) can be jointly delivered by the same carrier;
- the time window for leaving and going back to the depot for all carriers are the same. The request bundles are served in this time interval.

Figure 4.1 consider the example for study. All carriers are located at node 0. Nodes 1, 2, 3 are customer nodes that informed carriers will serve. The other nodes are lane requests for traded in CAs. All requests are one full truckload, no capacity constraints are concerned.

In other words,

- An informed carrier knows in advance that he needs to serve customers at nodes 1, 2, 3. A time window is given at each node and another time window at the node 0 for his truck to return. He will bid on the request bundles which allow him to go back to the depot with a cost reduction. For example, he serves the customer 2, he will choose a request bundles such as

Figure 4.1: Transportation network.



$r_{2 \rightarrow 4 \rightarrow 0}$ or $r_{2 \rightarrow 6 \rightarrow 4 \rightarrow 0}$ as long as they can reduce his cost and satisfy the time windows constraints. Informed carriers have to solve a cost minimization problem.

- A traditional carrier will bid on a request bundles with a tour such as $r_{0 \rightarrow 2 \rightarrow 6 \rightarrow 4 \rightarrow 0}$, $r_{0 \rightarrow 3 \rightarrow 7 \rightarrow 2 \rightarrow 0}$. Traditional carriers have to solve a profit maximization problem.
- for request lanes not taken for both carriers, they will be submitted to the spot market.

Notations

Let $G = (N, A)$ be a complete asymmetric graph where, $N = \{0, n + 1\}$ is the set of nodes, 0 is the depot, $n + 1$ is the destination and $A = \{(i, j) \mid i \neq j; i, j \in N\}$ is the set of undirected arcs.

Parameters:

- C_1 : set of informed carriers;
- C_2 : set of traditional carriers;
- C_3 : set of spot market carriers;
- $C = C_1 \cup C_2 \cup C_3$: set of all carriers;

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- R : set of requests;
- $RB_{c \in C}$: set of feasible bundle for carrier $c \in C$;
- o_r, d_r : origin and end node for a request $r \in R$;
- a_r, b_r : lower and upper bounds of the time window for request $r \in R$;
- s_c, t_c : lower and upper bounds of the time window for informed carrier $c \in C_2$ to cover his own request;
- t_r : duration to deliver the request $r \in R$;
- O : depot for all carriers;
- $O_{c \in C_1}$: set of customer locations for informed carrier $c \in C_1$;
- t_{ij} : traveling time for an empty move from i to j .

The feasible bundles for the carriers are defined as follows,

- For an informed carrier $c \in C_1$, let us assume that $rb = \{r_1, \dots, r_K\} \in RB_{c \in C_1}$ is a feasible bundle consisting of K requests. And $t_{r_{ks}}$ is the starting time for serving request r_k . The next constraints need to be satisfied:

$$\left\{ \begin{array}{l} t_{r_{ks}} \geq a_{r_k}; \forall k \in \{1, \dots, K\} \end{array} \right. \quad (4.1)$$

$$\left\{ \begin{array}{l} t_{r_{ks}} + t_{r_k} \leq b_{r_k}; \forall k \in \{1, \dots, K\} \end{array} \right. \quad (4.2)$$

$$\left\{ \begin{array}{l} s_c \leq t_{r_{1s}}; \end{array} \right. \quad (4.3)$$

$$\left\{ \begin{array}{l} \sum_{k=1}^{K-1} t_{r_{1s}} + t_{r_k} + t_{r_k r_{k+1}} + t_{r_K} + t_{r_K O} \leq t_c; \end{array} \right. \quad (4.4)$$

$$\left\{ \begin{array}{l} d_{r_K} = O; \end{array} \right. \quad (4.5)$$

$$\left\{ \begin{array}{l} o_{r_1} = O_c. \end{array} \right. \quad (4.6)$$

where (4.1), (4.2) assure that the requests can be served on time; (4.3), (4.4) guarantee that the request bundle can be served in carrier c 's time window; also (4.5), (4.6) guarantee that the first request leaves from an informed carriers' customer locations and returns to the depot at last.

4.3 Resolution of bundle construction problem

- For a traditional carrier $c \in C_2$, let us assume that $rb = \{r_1, \dots, r_K\} \in RB_{c \in C_2}$ is a feasible bundle consisting K requests. And $t_{r_{ks}}$ is the starting time for serving request r_k . The next constraints need to be satisfied:

$$\begin{cases} t_{r_{ks}} \geq a_{r_k}; & (4.7) \end{cases}$$

$$\begin{cases} t_{r_{ks}} + t_{r_k} \leq b_{r_k}; \forall k \in \{1, \dots, K\} & (4.8) \end{cases}$$

$$\begin{cases} d_{r_K} = o_{r_1} = O. & (4.9) \end{cases}$$

where (4.7), (4.8) guarantee that the requests can be served on time; and (4.9) guarantees that truck leaves and returns to the depot.

- For a spot-market carrier $c \in C_3$, the request bundles only need to satisfy the time constraints.

4.3 Resolution of bundle construction problem

The bundle construction problem associated with traditional carriers is a VRPTW (Baker & Schaffer, 1986). For informed carriers, the bundle-construction is a VRPTW with pickup and delivery with a single pickup vertex corresponding to the customer location (Gansterer *et al.*, 2017).

As computing a feasible bundle is already a difficult problem, we need make some assumptions to be able to determine the set of qualified feasible bundles.

4.3.1 Simplified requests network

One difficulty occurs when several requests contain the same node. For example, several requests may share the same node with different time constraints allowing several visits of this node. The problem can not be solved as shortest path problem or travelling sales man problem. Therefore the request is decomposed as shown in Figure 4.2.

The decomposition of the network leads also to the following *Specifications of our model*:

- Due to specific network structure, the distance between two nodes may equal to 0 (for example, one request's destination is the next request's origin). For large time windows, different orders of several requests may occurred (for

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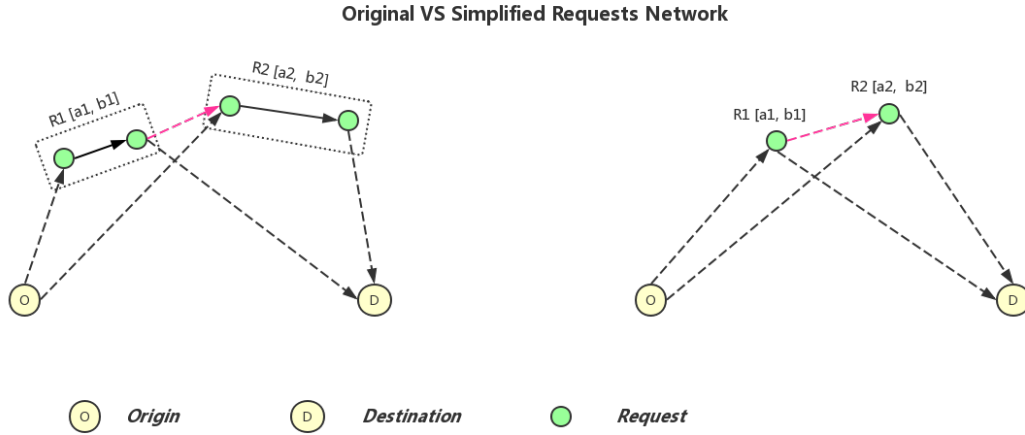


Figure 4.2: Example illustrates the transfer of original requests network to a simplified requests network.

example, two requests have the same origin/destination pair and large time windows) ;

- the simplified requests network is a complete asymmetric graph. Indeed, there is no order among the requests; and, $t_{ij} \neq t_{ji}$ for most of the cases of $(i, j), (j, i) \in A$.

Under these assumptions, the requests network is a complete asymmetric graph where the request nodes need to be visited within their time windows.

4.3.2 Bundle construction problem formulation

Let $G = (N, A)$ be a complete asymmetric graph where, $N = \{0, n + 1\}$ is the set of the request nodes, 0 is the depot, $n + 1$ is the destination and $A = \{(i, j) \mid i \neq j; i, j \in N\}$ is the set of undirected arcs.

Parameters:

- t_{ij} : travel time from node i to node j ;
- a_i : earliest visit (service begins) time of node i ;
- b_i : latest visit time of node i ;
- $[a_i, b_i]$: time window of node i ;

4.3 Resolution of bundle construction problem

- t_i : serving time at node i ;
- P_i : profit for serving node i ;
- c_{ij} : cost for traveling from node i to j .

Decision Variables:

- σ_t : service time at the t^{th} node of $N \cup \{0, n + 1\}$;
- y_{jt} : $y_{jt} = 1$ if node j is the t^{th} node of N in the Hamiltonian path, 0 otherwise;
- w_{ij}^t : $w_{ij}^t = 1$ if nodes i and j are respectively the $(t - 1)^{\text{st}}$ and t^{th} nodes of N in the Hamiltonian path*, 0 otherwise.

The BCP is formulated as follows:

$$\max \sum_{t=1}^n \left\{ \sum_{j \in N} P_j y_{jt} - \sum_{i, j \in N: i \neq j} c_{ij} w_{ij}^t \right\} \quad (4.10)$$

*A Hamiltonian path (or traceable path) is a path in an undirected or directed graph that visits each vertex exactly once.

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$$\begin{cases}
 \sigma_1 - \sigma_0 \geq \sum_{i,j \in N: i \neq j} t_{0j} w_{ji}^2 & (4.11) \\
 \sigma_t - \sigma_{t-1} \geq \sum_{i,j \in N: i \neq j} (t_i + t_{ij}) w_{ij}^t & t = 2, \dots, n+1 & (4.12) \\
 a_0 \leq \sigma_0 \leq b_0 & (4.13) \\
 a_{n+1} \leq \sigma_{n+1} \leq b_{n+1} & (4.14) \\
 \sigma_1 \geq \sum_{i,j \in N: i \neq j} a_j w_{ji}^2 & (4.15) \\
 \sigma_1 \leq \sum_{i,j \in N: i \neq j} (b_j - t_j) w_{ji}^2 & (4.16) \\
 \sigma_t \geq \sum_{i,j \in N: i \neq j} a_j w_{ij}^t & t = 2, \dots, n+1 & (4.17) \\
 \sigma_t \leq \sum_{i,j \in N: i \neq j} (b_j - t_j) w_{ij}^t & t = 2, \dots, n+1 & (4.18) \\
 \sum_{j \in N} y_{jt} \leq 1 & t = 1, \dots, n+1 & (4.19) \\
 \sum_{t=2}^{n+1} y_{jt} \leq 1 & j \in N & (4.20) \\
 \sum_{i \in N} w_{ij}^t = y_{jt} & j \in N, t = 2, \dots, n+1 & (4.21) \\
 \sum_{i \in N} w_{ji}^t = y_{j,t-1} & j \in N, t = 2, \dots, n+1 & (4.22) \\
 y_{jt} \in \{0, 1\} & j \in N, t = 2, \dots, n+1 & (4.23) \\
 w_{i,j}^t \geq 0 & i, j \in N (i \neq j), t = 2, \dots, n+1 & (4.24) \\
 y_{(n+1)(n+1)} = 1 & (4.25)
 \end{cases}$$

Constraints (4.11) and (4.12) are the schedule compatibility inequalities. Constraints (4.13) - (4.18) are the time windows inequalities. Constraints (4.19) and (4.20) are the flow inequalities: (4.19) imposes that a node is visited in each position $t = 1, \dots, n+1$, whereas (4.20) ensures that each node is visited at most once. Finally, constraints (4.21) and (4.22) link the transition y and position variables w .

4.4 Bounded exact bi-directional dynamic programming

In this section we describe a bounded bi-directional dynamic programming algorithm to compute a set of solutions with an order priority.

As described in [Righini & Salani \(2009\)](#) for the bounded bi-directional dynamic programming algorithm, a request node i corresponds to the state (S, τ, P, i, O) , where S is a binary vector representing the subset of request nodes already visited, τ is the time used, P is the profit collected, i is the last reached node, and O stores the path of this state with nodes order. The states of the nodes are extended in both forward from the origin 0 and backward from the destination $n + 1$. All states are generated respecting nearly half of the resource constraints (time, capacity, etc.). Joining forward and backward states yield to determine complete paths.

4.4.1 Forward and backward extension and extension rules

The extension of state (S, τ, P, i, O) associated with node i to node j results a new state (S', τ', P', j, O) according to the following rules,

- The profit P , initialized to 0 at node 0, is updated as

$$P' = P + \frac{P_i}{2} + \frac{P_j}{2} - c_{ij}$$

- The vector S is initialized to 0 and updated as

$$S'_k = \begin{cases} S_k + 1, & k = j \\ S_k, & k \neq j \end{cases}$$

A state (S, τ, P, i) can be extended to node j only if $S_j = 0$.

- The consumption of time resource τ is updated according to the type of the extension. Time window $[a_i^{bw}, b_i^{bw}]$ represents the backward time window of node i : determined by adding the service time t_i to the forward time window $[a_i, b_i]$ for each $i \notin \{0, n + 1\}$.

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For forward extensions:

$$\tau' = \max\{\tau + t_i + t_{ij}, a_j\}$$

and for backward extensions:

$$\tau' = \max\{\tau + t_j + t_{ij}, b_{n+1} - b_i^{bw}\}.$$

A forward state (S, τ, P, i) is feasible only if $\tau \leq b_i$; a backward state (S, τ, P, i) is feasible only if $\tau \leq b_{n+1} - a_i^{bw}$.

- The path O is initialized with the depart node. A new node j is added to i 's state only if it satisfies the feasibility check from i to j as we defined above.

4.4.2 Dominance test

Dominance tests are performed at each time when the states are extended. It keeps only the non-dominated states and reduces the computational efforts. Let $L_1 = (S_1, \tau_1, P_1, i, O_1)$, $L_2 = (S_2, \tau_2, P_2, i, O_2)$ be the labels of two states associated with node i generated in the same extended direction, and

$$|S| = \sum_{s \in N} S_i$$

Then L_1 dominates L_2 only if

$$\begin{cases} |S_1| \leq |S_2| \\ \tau_1 \leq \tau_2 \\ P_1 \geq P_2 \end{cases}$$

where at least one of the inequalities is strictly satisfied.

4.4.3 Matching forward and backward states

Forward and backward states are matched together to build full paths from node 0 to node $n+1$. The feasibility conditions to match forward path $(S^{fw}, \tau^{fw}, P^{fw}, i, O^{fw})$

4.4 Bounded exact bi-directional dynamic programming

with a backward path $(S^{bw}, \tau^{bw}, P^{bw}, j, O^{bw})$ are defined as:

$$\begin{cases} S_k^{fw} + S_k^{bw} \leq 1 & \forall k \in N \\ \tau^{fw} + t_i + t_{ij} + t_j + \tau^{bw} \leq b_{n+1}, \end{cases}$$

The overall profit of the resulting path is

$$P = P^{fw} + \frac{P_i}{2} + \frac{P_j}{2} + P^{bw} - c_{ij},$$

The resulting full path is obtained by joining the forward and backward state nodes order

$$O^{fw} + Reverse(O^{bw}).$$

The bounded bi-directional dynamic programming algorithm is defined in Algorithm 1. For each node $i \in N$, $\Gamma_i^{fw}/\Gamma_i^{bw}$ is the forward/backward set of labels associated with the node, $\overline{\Gamma}_i^{fw} \subseteq \Gamma_i^{fw}/\overline{\Gamma}_i^{bw} \subseteq \Gamma_i^{bw}$ is the subset of labels not extended so far, Δ_i^+/Δ_i^- denotes the set of successors of i in forward and backward extension. E is the set of nodes to be examined. $Extend(l_i, k)^{fw}/Extend(l_i, k)^{bw}$ corresponds to the extension procedure. The state l_i of node i specified as the first argument is extended to the node k specified as the second argument. This procedure follows the extension rules we defined above and checks the feasibility of the new states. $EFF(\Gamma, l)$ is the insertion procedure of state l into set $\overline{\Gamma}$ by applying the domination rules. Finally Θ contains all the joined paths.

4.4.4 Solution uniqueness and optimality

As discussed in Righini & Salani (2006), the dynamic programming algorithm defined in Algorithm 1 can result duplicate solutions if the resource constraints are not tight. For the BCP problem, if the time windows of the requests are large, requests can be present in both forward and backward states resulting duplicate solutions. Therefore, we add a remove procedure at the end of the matching procedure as defined in Algorithm 2. Θ^{new} indicates the new generated path pool.

Another issue comes from the optimality of the solution. Indeed, as the bi-directional dynamic programming stopped at the *HalfWay* of the resource constraints (Righini & Salani, 2006), it may not explore the whole structure of the

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Algorithm 1 Bounded Bi-directional Dynamic Programming

```

//Initialization//
 $\Gamma_i^{fw} \leftarrow \{0, 0, 0, 0, \{0\}\}$ 
 $\Gamma_i^{bw} \leftarrow \{0, 0, 0, 0, \{n+1\}\}$ 
for all  $i \in N \setminus \{0\}$  do
     $\Gamma_i^{fw} \leftarrow \emptyset$ 
for all  $i \in N \setminus \{n+1\}$  do
     $\Gamma_i^{bw} \leftarrow \emptyset$ 
 $E \leftarrow \{0, n+1\}$ 
 $\Theta \leftarrow \emptyset$ 
//Search//
repeat
    //Node selection//
    Select  $i \in E$ 
    //Forward extension//
    for all  $l_i = (S_i, \tau_i, P_i, i, O_i) \in \overline{\Gamma_i^{fw}}$  do
        for all  $j \in \Delta_i^+$  such that  $S_j^i = 0$  do
             $l_j \leftarrow \text{Extend}^{fw}(l_i, j)$ 
             $\Gamma_j^{fw} \leftarrow \text{EFF}(\Gamma_j^{fw}, l_j)$ 
            if  $\overline{\Gamma_j^{fw}} \neq \emptyset$  then
                 $E \leftarrow E \cup \{j\}$ 
    //Backward extension//
    for all  $l_i = (S_i, \tau_i, P_i, i, O_i) \in \overline{\Gamma_i^{bw}}$  do
        for all  $j \in \Delta_i^-$  such that  $S_j^i = 0$  do
             $l_j \leftarrow \text{Extend}^{bw}(l_i, j)$ 
             $\Gamma_j^{bw} \leftarrow \text{EFF}(\Gamma_j^{bw}, l_j)$ 
            if  $\overline{\Gamma_j^{bw}} \neq \emptyset$  then
                 $E \leftarrow E \cup \{j\}$ 
until  $E = \emptyset$ 
//Join forward and backward paths//
for all  $(S^{fw}, \tau^{fw}, P^{fw}, i, O^{fw}) \in \Gamma^{fw}$  do
    for all  $(S^{bw}, \tau^{bw}, P^{bw}, i, O^{bw}) \in \Gamma^{bw}$  do
        for all  $k \in N$  do
            if  $S_k^{fw} + S_k^{bw} \leq 1$  and  $\tau^{fw} + t_i + t_{ij} + t_j + \tau^{bw} \leq b_{n+1}$  then
                 $\Theta \leftarrow \Theta \cup \{O^{fw} + \text{Reverse}(O^{bw})\}$ 

```

Algorithm 2 Remove Procedure

```

//Initialization//
 $\Theta^{new} \leftarrow \emptyset$ 
//Generating new path pool//
repeat
  for all  $i \in \Theta$  do
    if  $i \notin \Theta^{new}$  then
       $\Theta^{new} = \Theta^{new} \cup \{i\}$ 
       $\Theta = \Theta \setminus \{i\}$ 
until  $\Theta = \emptyset$ 

```

instance. And result in non-optimal solutions.

4.5 Numerical results

4.5.1 Data-sets

Computational experiments are performed on the instances introduced by [Righini & Salani \(2009\)](#) for solving orienteering problem with time windows. According to the displacement of the nodes, these data sets are divided into *clustered*, *random* and *random – clustered* categories by considering the first 50 and 100 nodes (namely c101, r101 and rc101). Instances belonging to the same category have the same location and same lane requests. They differ only on the time windows.

4.5.2 Computational results

The algorithms were coded in Python 3.6 and the running time limit is set to 2 hours. To explore near optimal solutions, for the forward and backward extension, the time limit is set to $0.6T$ instead of *HalfWay* ($0.5T$), where T is the path time constraint. As in the works of [Righini & Salani \(2006, 2008, 2009\)](#), O is not considered which keeps the information about the order in which the nodes are visited, the computed time are relatively long and memory used are relatively large.

Numerical results are given in [Table 4.1](#). The first column reports the instance name, then second is the best known solution, the third is the profit, and the

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Instance	50 requests					100 requests				
	BestKnown	Profit	Gap(%)	Time(s)	nb of Paths	BestKnown	Profit	Gap(%)	Time(s)	nb of Paths
c101	270	270	0.00	0.35	7045	320	320	0.00	1.82	26599
c102	300	300	0.00	8.89	35851	360	360	0.00	60.48	271400
c103	320	310	3.13	27.69	93894	400	370	7.50	216.74	501315
c104	340	320	9.19	81.10	271501	420	410	2.38	574.89	<i>1296054</i>
c105	300	300	0.00	0.89	16646	340	340	0.00	5.73	79054
c106	280	280	0.00	0.51	8486	340	340	0.00	12.90	141493
c107	310	310	0.00	1.88	31146	370	370	0.00	13.59	190845
c108	320	320	0.00	3.18	52960	370	370	0.00	35.71	384371
c109	340	340	0.00	8.69	114890	380	380	0.00	68.20	629522
r101	126	129	-2.38	0.09	1825	198	198	0.00	1.44	15067
r102	198	200	-1.01	4.53	30891	286	286	0.00	69.64	294788
r103	214	211	1.40	19.64	128773	293	290	1.02	374.52	<i>1610067</i>
r104	227	229	-0.88	80.26	<i>492521</i>	303	301	0.66	886.91	<i>4295871</i>
r105	159	159	0.00	0.59	7911	247	247	0.00	13.40	151947
r106	208	205	1.44	7.31	63608	293	293	0.00	108.82	608598
r107	220	217	1.36	23.95	169013	299	297	0.66	450.63	<i>2227482</i>
r108	227	225	0.88	81.05	<i>515096</i>	308	305	0.97	993.83	<i>5153861</i>
r109	192	197	-2.60	3.56	37510	277	277	0.00	75.91	711592
r110	208	208	0.00	12.41	106512	284	281	1.06	236.80	<i>1467550</i>
r111	223	216	3.14	19.20	145005	297	289	2.69	362.95	<i>1687758</i>
r112	226	226	0.00	31.97	251192	298	289	3.02	705.21	<i>3275548</i>
rc101	180	190	-5.56	0.40	4680	219	219	0.00	6.24	66603
rc102	230	240	-4.35	1.35	13199	266	266	0.00	53.01	334328
rc103	240	250	-4.17	3.76	37111	266	266	0.00	154.45	<i>1157109</i>
rc104	270	270	0.00	12.00	106488	301	301	0.00	528.05	<i>3379175</i>
rc105	210	210	0.00	1.19	10475	244	244	0.00	39.06	256725
rc106	210	210	0.00	1.63	15740	252	252	0.00	56.19	414053
rc107	240	240	0.00	5.12	39003	277	277	0.00	155.32	998655
rc108	250	250	0.00	10.25	72158	298	298	0.00	367.14	<i>2060557</i>
Avg.			-0.014	16.79				0.688	231.04	

Table 4.1: Computational results for BCP with 50 and 100 requests

fourth is the percentage gap. The computed time in seconds and path number generated by using the bounded bidirectional dynamic programming for both 50 and 100 request nodes are given in column 5 and 6.

The DP algorithm solve all of Solomon’s instances with 50 and 100 request nodes within 2 hours. All instances with 50 nodes can be solved within less 2 minutes with a small average improvement of the best known solution. All instances with 100 nodes can be solved within 1000 seconds with a relatively small gap. For the hard instances, for example in 50 nodes case, r104 and r108, the remove procedure to delete the duplicate solutions is not performed due to the computational time (the results with italic format letters). However, according to the existing results, the duplicate solutions are no larger than 10% of the initial computed paths.

Note that, if we extend the searching space, the best found solution can be improved. For example, for the instance c103 and c104 of 50 nodes, when we extend the searching space to T, we can obtain the same profit as the Best-Known solution.

4.6 Conclusions

In this chapter, we define a new model in which a new type carrier (i.e. informed carrier) is introduced into the transportation service procurement market. The definition of the feasible request bundles for each carrier are given. The problem was solved by applying bounded exact bi-directional dynamic programming algorithm. Although three types of carriers are described in Section 3 but they are treated as one same model as the bundle construction problem, the pricing strategies generally differ from each other which will yield different benefits for shippers and carriers.

The contributions of this chapter are threefold: 1. a new carrier type called "informed carriers" is introduced in the transportation procurement who have several advantages in the competition with classical carriers; 2. a request network is considered in our model to avoid non-compatible solutions; 3. a bi-directional dynamic programming algorithm is developed to solve the problem, which provide us with a non-dominated solution set instead of only the optimal solution.

As mentioned in section 2, few research is devoted to less than full truckload freight transportation, the model developed in this paper can be extended when capacity is integrated in the routing construction problem where the request nodes can overlap from each other.

4. BUNDLE CONSTRUCTION PROBLEM IN CAS FOR FULL TRUCKLOAD TRANSPORTATION PROCUREMENT

Chapter 5

Single-leader Single-follower Pricing-Allocation Bilevel Model in CAs for Full Truckload Transportation Procurement

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The procurement of transportation services is an important task for shippers to control costs and provide high quality services. In the past, when shippers needed to procure transportation services for a set of lanes, they determined quotes for each lane individually and repeat the simple auction process for each lane, or they negotiated for bundles of lanes with one carrier at a time. This process is called "call-for-quote-and-negotiation procurement method". However, as software technology develops, all lanes can be bid simultaneously. Moreover, carriers can simultaneously bid upon combinations of individual lanes, leading to Combinatorial Auctions (CAs).

In the CAs framework, carriers are solving a price-based revenue management problem. They price a set of bundles/bids (of lane requests) for transportation procurement in order to maximize their total revenue. This problem is known as carrier's Optimal Bid Generation Problem (BGP) (Song & Regan, 2003a); while the auctioneer - generally the third party logistics - represents the shippers allocating bundles to carriers on the basis of their proposed bids. This problem refers to Winner Determination Problem (WDP) (Lehmann *et al.*, 2006).

The procedure defined in Song & Regan (2003a) for CAs consists in two phases:

- In the first phase, potential tours (bundles, bids of lane requests) are build. The tour is constructed by each carrier's operating abilities and while satisfying all relevant constraints. Potential tours are build as Bundle Construction Problem (BCP), see Chapter 4. Then the bundles are submitted to the auctioneer in the form of XOR bids (see Chapter 2.2.3) .
- In the second phase, a set partitioning model is defined based on binary variables to determine which bundles to select in the final allocation for the carriers.

In a single round auction procedure, no more bids are allowed after the WDP computation. For multiple rounds, bidders are allowed to submit bundles again after the WDP has been computed. The multiple round combinatorial auction

format could be an iterative ascending format e.g. the mechanism in [Parkes \(1999a\)](#), the prices are increasing and updated on the basis of bids from bidders that are not accepted in the current round of the auction. Multiple round auctions lead to better results than single round auctions in situations where the computational requirements to evaluate the worth of items is hard ([Parkes, 1999b](#)). The information, e.g. prices for bundles obtained after a round, can enable bidders to adjust their strategies and react to price changes.

In this thesis, as discussed in [2.4](#), the bilevel setting is used to build the pricing-allocation model in CAs. Introducing bilevel structure between carriers/BGP and auctioneer/WDP allows us to adequately formulate their sequential hierarchical relationships. At the upper level/leader, carriers **collaboratively** or **competitively** choose their pricing strategies, knowing that the lower level/auctioneer is going to adapt his behavior - allocation bundle of lanes to carriers - accordingly. In chapter 5 and 6, the single-leader single-follower and multi-leader single-follower bilevel models are discussed. In the single-leader single-follower bilevel model, carriers **collaboratively** determine their pricing strategies. In multi-leader single-follower bilevel model, carriers **competitively** choose their pricing strategies to maximize their own revenue.

For the rest of this chapter, we first introduce the definitions and basic assumptions. Next, we define the bilevel model describing the hierarchical relationship between leader and follower. Finally we present a solution algorithm and discuss numerical results.

5.1 Problem Definition

5.1.1 Assumptions, definitions and notations

We first give some definitions and define some assumptions:

- We only consider full truckload (FTL) carriers, thus substitutability among the lanes in a bundle will not be considered since one lane cannot be included by another;
- The lane request bundles are given by the Bundle Construction Problem(BCP) in Chapter [4](#). Note that, a lane is a transportation task with an

5. SINGLE-LEADER SINGLE-FOLLOWER PRICING-ALLOCATION BILEVEL MODEL IN CAS FOR FULL TRUCKLOAD TRANSPORTATION PROCUREMENT

origin - destination associated with a time window. A bundle is route with at least one transportation lane;

- The lane demands/requests are given before bundling and pricing, no future lanes arrives after the final allocation. This assumption is common for long distance, long term transportation tasks when they are not easy to exchange, reallocate which differs from the less than truckload (LTL) tasks;
- The prices proposed by carriers are either for bundles or for the individual request.

Definition 5.1 (Bundle Pricing Problem (Xia *et al.*, 2004)) *The bundle pricing Problem consists in computing a final price for each bundle.*

Remark 5.2 *A single price associated with each bundle but not with each individual lane, means that we do not need to care about the complementarity (or substitutability in a more general setting) among the lanes in a bundle.*

Definition 5.3 (Individual Pricing Problem) *The individual pricing problem consists in determining the final price for each individual lane. Individual lane prices can serve as benchmarks for combinatorial bids. Denote by $v_i(j)$ the final price of carrier i for lane j . The final price $v_i(S)$ for a bundle S is the sum of all lane prices included in this bundle,*

$$v_i(S) = \sum_{j \in S} v_i(j). \quad (5.1)$$

Proposition 5.4 *The bundle pricing problem is equivalent to the individual pricing only if the valuation is additive over lanes i.e. the lanes included in a bundle have no inter-relationships. With complementarity among the lanes in a bundle, the following inequality holds,*

$$v_i(S) \leq \sum_{j \in S} v_i(j). \quad (5.2)$$

In a more general setting, with substitutability among lanes in a bundle, the following inequality holds,

$$v_i(S) \geq \sum_{j \in S} v_i(j). \quad (5.3)$$

The goals to determine bundle prices for CAs are twofold (Xia *et al.*, 2004):

- *Market clearing goal:* The total surplus is maximized (so the allocation is efficient), and the final prices is a competitive equilibrium. More precisely, every bidder can improve his profit by selecting another bundle to trade other than the one he has been assigned. Note the definition of market clearing when imputing individual prices, shown in Definition 2.9, is different as the competitive equilibrium may not lead to the defined bids in 2.9.
- *Incentive compatibility:* Given the prices, there is no incentive for any individual bidder to misrepresent his valuation in order to improve his outcome.

The bundle and individual pricing strategies will be compared in the rest sections.

5.1.2 The shipper’s Winner Determination Problem (WDP)

The WDP problem consists in determining an allocation of items to bidders (the auctioneer can keep some of the items- not all items are given to bidders) given a set of bids in a CAs, such that the auctioneer’s revenue is maximized. For the transportation procurement problem, the auctioneer’s (shipper’s) objective is to minimize the total shipping cost, i.e. the sum of bidding prices of all bundles in the final allocation.

Let $N = \{1, \dots, n\}$ be the set of bidders (carriers) and let $V = \{1, \dots, m\}$ be the set of items (transportation lane requests). A bundle $S \subseteq V$ is a set of lanes. Let $\mathcal{F} = \mathcal{F}_1 \cup \dots \mathcal{F}_n$ be the set of all the bundles offered by at least one of the carriers, where \mathcal{F}_i is the bundle set proposed by carrier i . For a bundle S and a carrier i , we denote by $v_i(S)$ the bundle bid that carrier i makes for bundle S , i.e., the maximal price that i is willing to pay for S .

An allocation of the lanes is described by variables $x_i(S) \in \{0, 1\}$. The variable $x_i(S)$ is equal to one if and only if bidder i gets bundle S . An allocation $(x_i(S)|i \in N, S \in \mathcal{F})$ is said to be feasible if it allocates no lane more than once:

$$\sum_{i \in N} \sum_{S \in \mathcal{F}, S \ni j} x_i(S) \leq 1 \quad \forall j \in V, \tag{5.4}$$

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and at most one bundle to every carrier (XOR bidding language format)

$$\sum_{S \in \mathcal{F}} x_i(S) \leq 1 \quad \forall i \in N. \quad (5.5)$$

Definition 5.5 Winner Determination Problem (WDP)

Given bids $\{v_i, i = 1, \dots, n\}$, the winner determination problem is defined as

$$x \in \operatorname{argmin} \left(\sum_{i \in N} v_i(S) x_i(S) \mid x \text{ is a feasible allocation} \right). \quad (5.6)$$

This problem determines the final allocations for carriers. Multiple solutions may exist.

5.1.3 The carrier's optimal Bidding Generation Problem (BGP)

In transportation procurement context, the carriers' major goal is to take advantage of inter-dependencies in their transportation operations when determining the optimal bundles to bid for.

The carrier i 's optimal bidding generation problem is defined as:

$$\max_{v_i(S)} \sum_{S \in \mathcal{F}} (v_i(S) - \operatorname{OperC}_i(S)) x_i(S) \quad (5.7)$$

$$s.t. \begin{cases} \text{Price bounding constraints} & (5.8) \\ \text{Resource constraints} & (5.9) \end{cases}$$

The price bounding constraints define the price interval where the lower bound is 0 and the upper bound is the market price. The resource constraints defines the resources owned by carrier, such as, number of trucks, available traveling times, etc... The "Operation cost" for a bundle S given as $\operatorname{OperC}_i(S)$ could vary a lot, opportunity costs in Figliozzi *et al.* (2006); empty equipment re-positioning costs in Zhou & Lee (2009); or the transportation costs itself.

In transportation procurement problem, each carrier has to solve an optimal BGP, such that, they have to decide in a *cooperative/competitive manner*,

- which bundles to bid on;

5.1 Problem Definition

- the price associated with each bundle;
- the parameters for their operation cost.

We now discuss the bidding generation problem for informed carrier. An informed carrier is a carrier offering truck resource between two empty truck move nodes. More precisely, he is interested by adding new lanes in his pre-existing network between two nodes. We now describe 2 examples. In example 1, after serving his customer at Paris, a carrier has an empty truck departing from Paris to Nice with a large time windows. It is better for him to serve some transportation requests (bundle) in between. he prefers to take some profitable transportation requests (a bundle) rather than only the empty truck. In second example (see Figure 5.1), a carrier has a tour including 4 requests. To add one or several of the new (gray) requests will probably result extra profit.

We denote by $V_i(S)$ the maximum price that a carrier i can offer for a bundle S , then

$$V_i(S) = \sum_{j \in S} V(j) \quad (5.10)$$

where $V(j)$ is given as the marginal price that each carrier can offer for a lane j .

The optimal bidding generation problem for informed carrier is defined by:

$$\max_{v_i(S)} \sum_{S \in \mathcal{F}_i} (v_i(S) - \text{OperC}_i(S))x_i(S) - z_i \overline{\text{OperC}_i(\mathcal{F}_i)} \quad (5.11)$$

$$s.t. \begin{cases} v_i(S) \leq V_i(S) & (5.12) \\ \sum_{S \in \mathcal{F}_i} x_i(S) + z_i = 1 & (5.13) \end{cases}$$

The objective of the informed carrier is to cover a bundle to reduce their cost from a location pair o to d . In (5.11), the first term is the profit if the informed carrier covers a bundle S from origin o to destination d , otherwise he goes from o to d with an empty truck, and he pays $\overline{\text{OperC}(\mathcal{F}_i)}$. Constraint (5.12) is the bounding constraints where $V(S)$ is the market highest price. Constraint (5.13) is the path constraints: a carrier either goes from o to d with an empty truck or with a bundle, z_i equals to one only there is no bundle assigned to carrier i .

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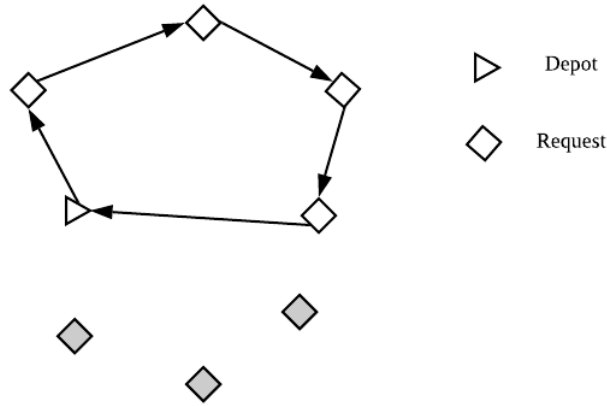


Figure 5.1: Informed carrier with a tour with 4 requests. Including one of the new (gray) requests will probably result extra profit.

5.2 Price update and bilevel formulation for informed carriers

Pricing problems perfectly fit the bilevel framework when player/follower in the system is sensitive to the price changes and will react differently, then the price proposer/leader has to determine an optimal pricing strategy with knowing the follower's reaction. Pricing bilevel models have been studied by [Brotcorne *et al.* \(2001\)](#); [Heilporn *et al.* \(2010\)](#); [Labbé *et al.* \(1998\)](#) as toll-setting problems, in [Afşar *et al.* \(2016\)](#); [Aussel *et al.* \(2017, 2019\)](#) as energy pricing problems, in [Gilbert *et al.* \(2015\)](#); [Labbé & Violin \(2013\)](#); [Marcotte & Savard \(2002\)](#); [Robbins & Lunday \(2016\)](#) as pricing-setting problem, etc... As mentioned in [Gansterer & Hartl \(2017, 2018\)](#), classically, in the literature, CAs, BGP and WDP are studied separately. There is no solution for the whole system (5-phase procedure for CAs) in an auction-based decentralized planning, the pricing strategies are either based on marginal price or a given pricing strategy as described in Section 2.3.1.2.

5.2.1 Price update and bilevel formulation

The bidder's optimization problem is a pricing problem derived from a WDP allocation as an input. A bilevel optimization problem is solved to obtain prices for bundles.

5.2 Price update and bilevel formulation for informed carriers

In the bilevel problem, the auctioneer's allocation is solved at the lower level. Carriers at the upper level solve the revenue management problem to maximize their profits explicitly integrating the reaction of the lower level in their decision making process.

We next define the notations,

Given data:

- A graph $G = (V, E)$, where $V = \{1, \dots, m\}$ is the set of lanes and E is the set of edges connecting the lanes;
- $N = \{1, \dots, n\}$ the set of carriers;
- A bundle S is a set of lanes: $S \subseteq V$;
- $\mathcal{F} = \mathcal{F}_1 \cup \dots \mathcal{F}_n$ is the set of all the bundles demanded by at least one of the carriers. \mathcal{F}_i is the bundle set proposed for carrier i ;
- $\overline{\text{OperC}_i(\mathcal{F}_i)}$ is the operation cost if carrier i does not cover any transportation request;
- $\text{OperC}_i(S)$ is the operation cost for carrier i to cover bundle S ;
- V_j is the price of the lane j if it is served by the spot market;
-

$$\delta_{jS} = \begin{cases} 1 & \text{if lane } j \in S \\ 0 & \text{otherwise} \end{cases} \quad (5.14)$$

$$\delta_{jS} = \begin{cases} 1 & \text{if lane } j \in S \\ 0 & \text{otherwise} \end{cases} \quad (5.15)$$

The decision variable are:

•

$$x_i(S) = \begin{cases} 1 & \text{if bundle } S \text{ is assigned to carrier } i \\ 0 & \text{otherwise} \end{cases} \quad (5.16)$$

$$x_i(S) = \begin{cases} 1 & \text{if bundle } S \text{ is assigned to carrier } i \\ 0 & \text{otherwise} \end{cases} \quad (5.17)$$

•

$$y_j = \begin{cases} 1 & \text{if lane } j \text{ is not covered by a carrier} \\ 0 & \text{otherwise} \end{cases} \quad (5.18)$$

$$y_j = \begin{cases} 1 & \text{if lane } j \text{ is not covered by a carrier} \\ 0 & \text{otherwise} \end{cases} \quad (5.19)$$

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•

$$z_i = \begin{cases} 1 & \text{if carrier } i \text{ is covering no bundle} \\ 0 & \text{otherwise} \end{cases} \quad (5.20)$$

$$(5.21)$$

- $v_i(S)$, the price determined by carrier i for bundle S . The valuation carrier i gives for a bundle S should be smaller than the summation of the spot market prices of the lanes contained in S

$$v_i(S) \leq V(S) = \sum_{j \in S} V_j \quad (5.22)$$

The single-leader single-follower bilevel formulation where the lower level problem is to maximize the summation of all carriers' overall profits is defined as follows,

$$\min_{x,y} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} v_i(S) x_i(S) + \sum_{j \in V} V_j y_j \quad (5.23)$$

$$s.t. \left\{ \begin{array}{l} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) \leq 1 \quad \forall j \in V, \\ \sum_{S \in \mathcal{F}_i} x_i(S) \leq 1 \quad \forall i \in N, \\ \sum_{S \in \mathcal{F}} \sum_{i \in N} \delta_{jS} x_i(S) + y_j = 1 \quad \forall j \in V, \\ \max_v \sum_{i \in N} \sum_{S \in \mathcal{F}_i} (v_i(S) - \text{OperC}_i(S)) x_i(S) - z_i \overline{\text{OperC}_i(\mathcal{F}_i)} \\ v_i(S) \leq V(S) \quad \forall i \in N, \forall S \in \mathcal{F}_i, \\ \sum_{S \in \mathcal{F}_i} x_i(S) + z_i = 1 \quad \forall i \in N. \end{array} \right. \quad (5.24)$$

$$\sum_{S \in \mathcal{F}_i} x_i(S) \leq 1 \quad \forall i \in N, \quad (5.25)$$

$$\sum_{S \in \mathcal{F}} \sum_{i \in N} \delta_{jS} x_i(S) + y_j = 1 \quad \forall j \in V, \quad (5.26)$$

$$\max_v \sum_{i \in N} \sum_{S \in \mathcal{F}_i} (v_i(S) - \text{OperC}_i(S)) x_i(S) - z_i \overline{\text{OperC}_i(\mathcal{F}_i)} \quad (5.27)$$

$$v_i(S) \leq V(S) \quad \forall i \in N, \forall S \in \mathcal{F}_i, \quad (5.28)$$

$$\sum_{S \in \mathcal{F}_i} x_i(S) + z_i = 1 \quad \forall i \in N. \quad (5.29)$$

At the upper level, the auctioneer decides which bundle $S \in \mathcal{F}$ to assign to each carrier $i \in N$. $x_i(S) = 1$ when bundle S is assigned to carrier i , $x_i(S) = 0$ otherwise. If a lane $j \in V$ is not assigned to the carrier, it is transferred to the spot market with cost V_j . Constraint (5.24) insures that each lane can only be assigned once. Constraint (5.25) insures that each carrier can at most get one

5.2 Price update and bilevel formulation for informed carriers

bundle (XOR bidding format). Constraint (5.26) guarantees that each request is either assigned to carriers or transferred to the spot market.

Constraint (5.28) is the price bounding constraint: the price defined by the carrier should be positive and smaller than the limited market price. Constraint (5.29) means that the carrier either cover a bundle or take nothing.

In this model, auctioneer at the upper level solve the minimization problem to allocate the bundles to the carriers in order to cover as much as lane requests; and carriers adjust their pricing strategies and maximize their profits at the lower level.

5.2.2 Reformulation as a single level optimization problem

As mentioned in Section 2.4.3, the classical approach to solve a bilevel optimization problem is to reformulate it as a single level optimization problem by replacing the lower level by its optimality conditions. As the lower level is linear programs (LP), its optimality conditions are equivalent to the primal feasibility, dual feasibility and complementary constraints.

The lower level problem - the optimal bidding generation problem - for carrier i can be simplified as follows:

Primal

$$\max_{v_i(S)} \sum_{S \in \mathcal{F}_i} v_i(S) x_i(S) \quad (5.30)$$

$$s.t. \quad v_i(S) \leq V(S) \quad S \in \mathcal{F}_i \quad (5.31)$$

The dual formulation corresponding to the primal problem is as follows:

Dual

$$\min_{\mu_i(S)} \sum_{S \in \mathcal{F}_i} V(S) \mu_i(S) \quad (5.32)$$

$$s.t. \quad \mu_i(S) \geq x_i(S) \quad S \in \mathcal{F}_i \quad (5.33)$$

Remark 5.6 *The dual of the lower level problem means that when the allocation at the upper level is done, the lower level will always choose the highest allowed price. It indicates that, if we model the auctioneer/shipper at the upper level, the reaction of the carriers will be always the highest allowed price and the decision*

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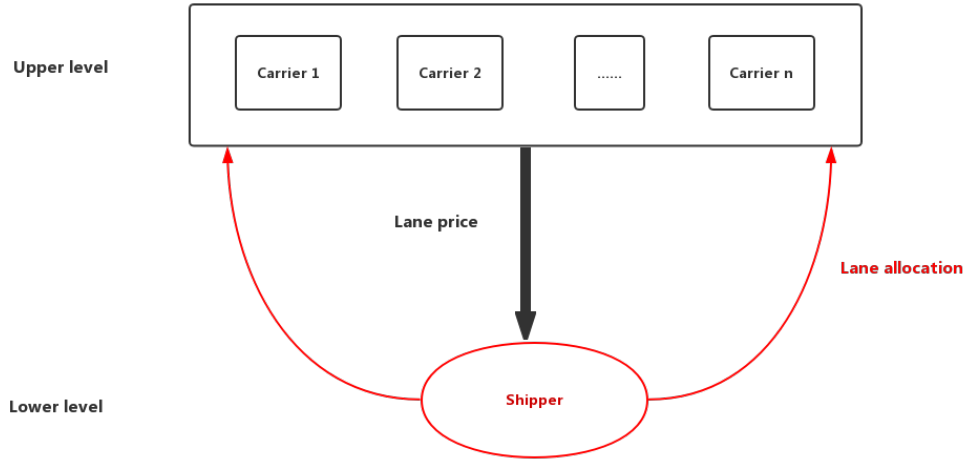


Figure 5.2: Illustration of the proposed model between carriers and shipper.

making orders are not corresponding the realistic situation. This does not reveal the fact that the the leadership of the auctioneer.

5.3 Second bilevel model

In a demand-response system (Cui *et al.*, 2016), the decision of the lower level is a response to the upper level's decision. More precisely, the auctioneer's decision - the allocation - depends on the bidder's decision - the prices, putting the auctioneer at the lower level and taking the auctioneer's decision as the a response to the upper level's decision will be more appropriate to formulate the relationship between bidder and auctioneer.

In this section, the notations are the same as in last section. We define the carriers maximization problem as the upper level problem, see Figure 5.2, they set bundle prices in response to the decision of the shipper's allocation at the lower level. In this formulation, the constraint (5.28) is omitted since the price of the lane j is bounded with the price V_j in the objective function, i.e. if the carriers propose a price higher than the spot market, the lane will be assigned to spot market*.

*This argument is true only in the case of individual lane pricing, in bundle pricing approach, we cannot evaluate the true value of a individual lane.

This formulation is as follows,

$$\max_v \sum_{i \in N} \sum_{S \in \mathcal{F}_i} (v_i(S) - \text{OperC}_i(S)) x_i(S) - z_i \overline{\text{OperC}_i(\mathcal{F}_i)} \quad (5.34)$$

$$\left\{ \begin{array}{l} \sum_{S \in \mathcal{F}_i} x_i(S) + z_i = 1 \quad \forall i \in N, \end{array} \right. \quad (5.35)$$

$$\left\{ \begin{array}{l} \min_x \sum_{i \in N} \sum_{S \in \mathcal{F}_i} v_i(S) x_i(S) + \sum_{j \in V} V_j y_j \end{array} \right. \quad (5.36)$$

$$\left\{ \begin{array}{l} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) \leq 1 \quad \forall j \in V, \end{array} \right. \quad (5.37)$$

$$\left\{ \begin{array}{l} \sum_{S \in \mathcal{F}_i} x_i(S) \leq 1 \quad \forall i \in N, \end{array} \right. \quad (5.38)$$

$$\left\{ \begin{array}{l} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) + y_j = 1 \quad \forall j \in V, \end{array} \right. \quad (5.39)$$

$$\left\{ \begin{array}{l} x_i(S), y_j, z_i \in \{0, 1\} \quad \forall i \in N, \forall S \in \mathcal{F}_i, \forall j \in V. \end{array} \right. \quad (5.40)$$

The variables y, z in this formulation can be easily replaced by the variable x ,

$$y_j = 1 - \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) \quad (5.41)$$

and

$$z_i = 1 - \sum_{S \in \mathcal{F}_i} x_i(S). \quad (5.42)$$

5.3.1 Lower level problem

The objective function of the lower level problem is given by

$$\min_x \sum_{i \in N} \sum_{S \in \mathcal{F}_i} v_i(S) x_i(S) + \sum_{j \in V} V_j y_j \quad (5.43)$$

$$= \min_x \sum_{i \in N} \sum_{S \in \mathcal{F}_i} v_i(S) x_i(S) + \sum_{j \in V} V_j (1 - \sum_{S \in \mathcal{F}} \sum_{i \in N} \delta_{jS} x_i(S)) \quad (5.44)$$

$$= \min_x \sum_{i \in N} \sum_{S \in \mathcal{F}_i} v_i(S) x_i(S) - \sum_{j \in V} \sum_{S \in \mathcal{F}} \sum_{i \in N} P_j \delta_{jS} x_i(S) + \sum_{j \in V} V_j \quad (5.45)$$

$$= \min_x \sum_{i \in N} \sum_{S \in \mathcal{F}_i} (v_i(S) - \sum_{j \in S} V_j \delta_{jS}) x_i(S) + \sum_{j \in V} V_j \quad (5.46)$$

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Step 5.45 to 5.46 are based on the fact $\delta_{jS} = 1$ only when $j \in S$. The summation $\sum_{j \in V}$ can be replaced by $\sum_{j \in S}$ and put in the inner summation when all the bundle $S \in \mathcal{F}$ are considered. In addition, for the lower level problem, $v_i(S)$, δ_{jS} and V_j are fixed, the objective of the lower level lead to the next simplification,

$$\min_x \sum_{i \in N} \sum_{S \in \mathcal{F}_i} c_{iS} x_i(S) \quad (5.47)$$

where

$$c_{iS} = v_i(S) - \sum_{j \in S} P_j \delta_{jS} \quad (5.48)$$

Finally, the lower level problem is defined as,

$$\min_x \sum_{i \in N} \sum_{S \in \mathcal{F}_i} c_{iS} x_i(S) \quad (5.49)$$

$$s.t. \begin{cases} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) \leq 1 & \forall j \in V, \\ \sum_{S \in \mathcal{F}_i} x_i(S) \leq 1 & \forall i \in N, \\ x_i(S) \in \{0, 1\} & \forall i \in N, \forall S \in \mathcal{F}. \end{cases} \quad (5.50)$$

The lower level is a weighted set partitioning problem with additional constraints (5.50) meaning that each request $j \in V$ can be at most covered once. As the lower level problem - the set partitioning problem - is not convex, continuous or with nice properties 2.4.3, it falls into the hardest case of the bilevel problems and it is NP-complete.

5.3.2 Special case of the problem: 1-to-1 pricing-allocation

In this section, we consider a special case where bundles are individual requests, the number of bundles are identical to the number of requests, the number of carriers $m = n$, all the carriers have the same bundle pool $\mathcal{F}_i = \mathcal{F} = \{\{1\}, \{2\}, \dots, \{m\}\}, \forall i \in N$, see Figure 5.3.

The lower level is a linear assignment problem, where each carrier is assigned at most one bundle, i.e. one request. The decision variables are doubled for both

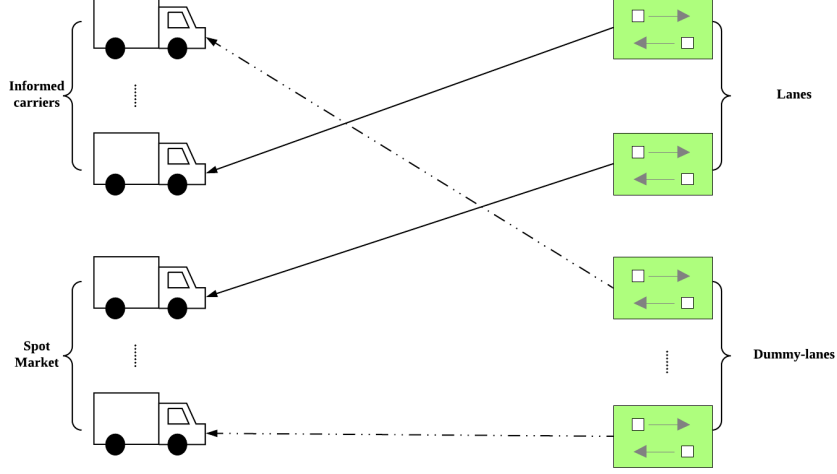


Figure 5.3: 1-to-1 pricing-allocation

dummy lanes and dummy carriers, i.e. spot market. More precisely, if one carrier covers no request, then he gets a dummy lane, and if one request is not covered by any carriers, it goes to spot market.

The bilevel model is given by,

$$\max_v \sum_{i=1}^n \sum_{j=1}^m (v_i(j) - \text{OperC}_i(j)) x_i(j) - \sum_{i=1}^n \sum_{j=1}^m \overline{\text{OperC}_i(\mathcal{F}_i)} x_i(m+j) \quad (5.53)$$

$$\min_x \left\{ \sum_{j=1}^m \sum_{i=1}^n v_i(j) x_i(j) + \sum_{j=1}^m \sum_{i=1}^n V_j x_{n+i}(j) \right. \quad (5.54)$$

$$s.t. \left\{ \sum_{i=1}^{2n} x_i(j) = 1 \quad \forall j \in \{1, \dots, 2m\}, \quad (5.55)$$

$$\sum_{j=1}^{2m} x_i(j) = 1 \quad \forall i \in \{1, \dots, 2n\}, \quad (5.56)$$

$$\left. x_i(j) \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{1, \dots, 2m\}. \quad (5.57) \right.$$

Since each carrier - including the dummy carriers - will be assigned with exactly one request - including the dummy requests, the factor $-z_i \overline{\text{OperC}_i(\mathcal{F}_i)}$ is replaced by $-\sum_{i=1}^n \sum_{j=1}^m \overline{\text{OperC}_i(\mathcal{F}_i)} x_i(m+j)$ in the upper level objective

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function. If there is no assignment for a non-dummy carrier i i.e. $x_i(j) = 0, \forall j \in \{1, \dots, m\}$, he will be assigned with a dummy lane j such that $x_i(j) = 1, \exists j \in \{m + 1, \dots, 2m\}$, it leads to the constraints 5.56, more precisely, each carrier can be assigned with exactly one lane, and it corresponds to a cost $\overline{\text{OperC}}_i(\mathcal{F}_i)$ in the upper level objective. Similarly, if a non-dummy lane j is not assigned to a non-dummy carrier, then $x_i(j) = 0, \forall i \in \{1, \dots, n\}$ and this lane will go to a dummy carrier/spot market ($x_i(j) = 1, \exists i \in \{n + 1, \dots, 2n\}$), it leads to the constraint 5.55. In other words, each lane can be assigned with exactly once, and it corresponds to a cost V_j in the lower level objective. In conclusion, the lower level problem is a one-to-one assignment problem. The binary variable constraints at the lower level can be relaxed as continuous due to the fact that the constraint matrix is totally unimodular (Carpaneto & Toth, 1987).

The lower level problem is thus a linear and convex problem. It can be replaced by its optimality conditions, i.e. the primal feasibility, dual feasibility and complementary feasibility.

Primal

$$\min_x \sum_{j=1}^m \sum_{i=1}^n v_i(j)x_i(j) + \sum_{j=1}^m \sum_{i=1}^n V_j x_{n+i}(j) \quad (5.58)$$

$$s.t. \begin{cases} \sum_{i=1}^{2n} x_i(j) = 1 & \forall j \in \{1, \dots, 2m\}, \\ \sum_{j=1}^{2m} x_i(j) = 1 & \forall i \in \{1, \dots, 2n\}, \\ x_i(j) \geq 0 & \forall i \in \{1, \dots, 2n\}, j \in \{1, \dots, 2m\}. \end{cases} \quad (5.59)$$

$$\sum_{j=1}^{2m} x_i(j) = 1 \quad \forall i \in \{1, \dots, 2n\}, \quad (5.60)$$

$$x_i(j) \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{1, \dots, 2m\}. \quad (5.61)$$

Associated with this primal problem there is a corresponding dual problem given by Carpaneto & Toth (1987):

Dual

$$\max_{\mu_i, \nu_j} \sum_{i=1}^{2n} \mu_i + \sum_{j=1}^{2m} \nu_j \quad (5.62)$$

$$s.t. \begin{cases} v_i(j) - \mu_i - \nu_j \geq 0 & \forall i \in \{1, \dots, n\}, j \in \{1, \dots, m\}, \\ V_j - \mu_i - \nu_j \geq 0 & \forall i \in \{n + 1, \dots, 2n\}, j \in \{1, \dots, m\}, \\ -\mu_i - \nu_j \geq 0 & \forall i \in \{1, \dots, 2n\}, j \in \{m + 1, \dots, 2m\}, \\ \mu_i, \nu_j \geq 0 & \forall i \in \{1, \dots, 2n\}, j \in \{1, \dots, m\}. \end{cases} \quad (5.63)$$

$$V_j - \mu_i - \nu_j \geq 0 \quad \forall i \in \{n + 1, \dots, 2n\}, j \in \{1, \dots, m\}, \quad (5.64)$$

$$-\mu_i - \nu_j \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{m + 1, \dots, 2m\}, \quad (5.65)$$

$$\mu_i, \nu_j \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{1, \dots, m\}. \quad (5.66)$$

The dummy lane involved in the dual problem is associated with 0 valuation

leading to the constraint 5.65, together with constraint 5.66. The associated $\mu_i, \forall i \in \{1, \dots, 2n\}$ and $\nu_j, \forall j \in \{m + 1, \dots, 2m\}$ are forced with the value 0. Thus the dual problem can be then simplified as:

Dual+

$$\max_{\nu_j} \sum_{j=1}^{2m} \nu_j \tag{5.67}$$

$$s.t. \begin{cases} v_i(j) - \nu_j \geq 0 & \forall j \in \{1, \dots, m\}, \\ V_j - \nu_j \geq 0 & \forall j \in \{1, \dots, m\}, \\ \nu_j \geq 0 & \forall j \in \{1, \dots, m\}. \end{cases} \tag{5.68}$$

$$\tag{5.69}$$

$$\tag{5.70}$$

5.3.2.1 Optimistic and pessimistic single level formulation

The bilevel problem (Colson *et al.*, 2007) has a natural interpretation as a non-cooperative game between two levels. Players at the upper level (leaders) choose his decision $v_i(j)$ i.e. c_{ij} first, then players at lower level (followers) observes c_{ij} and responds with a decision x . Both the objective function and the feasible region of the follower may depend on the leader's decision. Likewise, the leader has to satisfy a constraint that depends on the follower's decision. Since the leader cannot anticipate the follower's decision, the constraint must be satisfied for any rational decision of the follower, that is, for any feasible decision x that optimizes the follower's objective function. This statement leads to a pessimistic bilevel problem where the leader have to face the worst case that may happen to him, this problem is perceived to be very difficult to solve.

As a result, most theoretical and algorithmic contributions to bilevel programming relate to the optimistic formulation, in which the universal quantifier " \forall " in the bilevel constraint is replaced with an existential quantifier " \exists ". In a game theoretic context, the optimistic problem can be justified in two ways. On one hand, there may be limited cooperation between the players to the extent that the followers altruistically chooses an optimal solution that also benefits the leader. On the other hand, the leaders may be able to make small side payments that bias the follower's objective in his favor. Even though the optimistic and the pessimistic bilevel problem are very similar, their optimal solutions can differ considerably.

The bilevel formulation of the problem is formulated as a single level optimistic optimization problem where the lower level will always select the solution that is

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most favorable to the leader when facing several optimal solutions:

$$\max_v \max_x \sum_{i=1}^n \sum_{j=1}^m (v_i(j) - \text{OperC}_i(j)) x_i(j) - \sum_{i=1}^n \sum_{j=1}^m \overline{\text{OperC}_i(\mathcal{F}_i)} x_i(m+j) \quad (5.71)$$

$$\left\{ \begin{array}{l} \sum_{j=1}^m \sum_{i=1}^n v_i(j) x_i(j) + \sum_{j=1}^m \sum_{i=1}^n V_j x_{n+i}(j) = \sum_{i=1}^{2n} \mu_i + \sum_{j=1}^{2m} \nu_j \quad (5.72) \\ \sum_{i=1}^{2n} x_i(j) = 1 \quad \forall j \in \{1, \dots, 2m\}, \quad (5.73) \\ \sum_{j=1}^{2m} x_i(j) = 1 \quad \forall i \in \{1, \dots, 2n\}, \quad (5.74) \\ v_i(j) - \mu_i - \nu_j \geq 0 \quad \forall i \in \{1, \dots, n\}, j \in \{1, \dots, m\}, \quad (5.75) \\ V_j - \mu_i - \nu_j \geq 0 \quad \forall i \in \{n+1, \dots, 2n\}, j \in \{1, \dots, m\}, \quad (5.76) \\ -\mu_i - \nu_j \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{m+1, \dots, 2m\}, \quad (5.77) \\ \mu_i, \nu_j \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{1, \dots, m\}. \quad (5.78) \end{array} \right.$$

This bilevel formulation of the problem is formulated as a single level pessimistic optimization problem where the upper level consider the worst case that it may happen to him:

$$\max_v \min_x \sum_{i=1}^n \sum_{j=1}^m (v_i(j) - \text{OperC}_i(j)) x_i(j) - \sum_{i=1}^n \sum_{j=1}^m \overline{\text{OperC}_i(\mathcal{F}_i)} x_i(m+j) \quad (5.79)$$

$$\begin{cases}
 \sum_{j=1}^m \sum_{i=1}^n v_i(j)x_i(j) + \sum_{j=1}^m \sum_{i=1}^n V_j x_{n+i}(j) = \sum_{i=1}^{2n} \mu_i + \sum_{j=1}^{2m} \nu_j & (5.80) \\
 \sum_{i=1}^{2n} x_i(j) = 1 \quad \forall j \in \{1, \dots, 2m\}, & (5.81) \\
 \sum_{j=1}^{2m} x_i(j) = 1 \quad \forall i \in \{1, \dots, 2n\}, & (5.82) \\
 v_i(j) - \mu_i - \nu_j \geq 0 \quad \forall i \in \{1, \dots, n\}, j \in \{1, \dots, m\}, & (5.83) \\
 V_j - \mu_i - \nu_j \geq 0 \quad \forall i \in \{n+1, \dots, 2n\}, j \in \{1, \dots, m\}, & (5.84) \\
 -\mu_i - \nu_j \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{m+1, \dots, 2m\}, & (5.85) \\
 \mu_i, \nu_j \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{1, \dots, m\}. & (5.86)
 \end{cases}$$

In the optimistic case, the leader will always set the highest spot market price. Indeed, for a given set of requests and carriers, the solution strategies are finite, the leader defines the prices, and the follower give the cooperative allocation. No matter what the leader do (in the sense that the carriers can only decrease the prices of the requests), it will at least beneficial for the follower and it will not yield out better solution for the leader i.e. the solution strategies are the same and decreasing the prices will not lead higher profit for the leader.

In the pessimistic case, the maximization of the leader's objective not only depends on his own decision $v_i(j)$ but also on the worst response decision $x_i(j)$ from the follower. The solution given in this case guarantees the lowest profit for the leader.

5.3.2.2 Illustration between the optimistic and pessimistic cases

We next illustrate the difference between the optimistic and pessimistic cases on a small example. We consider two carriers and two request lanes i.e. two bundles, and the prices must be integers.

The lane information and solutions are reported in Table 5.1 and 5.2. The final allocation and defined prices are marked in red color.

As shown in Table 5.2, carrier 1 does not put the highest price on request 2, because the shipper is facing the same price over the two carriers. He will then

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Carrier	Lane	Market Price	Operation Cost	Optimal Solution
1	1	5	-1	5
	2	6	-1	6
2	1	5	-1	5
	2	6	-3	6

Table 5.1: Solution for the optimistic case of 1-to-1 pricing-allocation.

Carrier	Lane	Market Price	Operation cost	Optimal solution
1	1	5	-1	5
	2	6	-1	5
2	1	5	-1	5
	2	6	-3	6

Table 5.2: Solution for the pessimistic case of 1-to-1 pricing-allocation.

allocate randomly the two requests to the carriers. The cost of carrier 2 covering request 2 is higher.

Remark 5.7 *The pessimistic bilevel formulation is suitable for the transportation procurement. At the upper level, carriers set the incentive prices not only to lead the shipper's allocation over the transportation requests, but also to maximize their own profit.*

5.3.3 General case of the bilevel problem

In general, bilevel programming problems are difficult due to their non-convexity and non-differentiability. Most of the research has focused on the problems with nice properties such as linear, quadratic or convex objective and/or constraint functions. In such cases bilevel programs, the second level problems can be replaced by their optimality conditions. As for the integer bilevel programs, studies are very limited to find which has been devoted to the case where the objective/constraint functions of both levels are linear (Fischetti *et al.*, 2017; Tahernejad *et al.*, 2016).

In our bilevel model listed from (5.34) - (5.40), by replacing $z_i = 1 - \sum_{S \in \mathcal{F}_i} x_i(S)$ in and considering only bundle price, we obtain the following single-level bi-linear

optimization problem:

UP:

$$\min_{v,x} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \left(-v_i(S) + \text{OperC}_i(S) - \overline{\text{OperC}_i(\mathcal{F}_i)} \right) x_i(S) + \sum_{i \in N} \overline{\text{OperC}_i(\mathcal{F}_i)} \quad (5.87)$$

$$s.t. \begin{cases} 0 \leq v_i(S) \leq \sum_{j \in S} V_j & \forall i \in N, \end{cases} \quad (5.88)$$

$$\begin{cases} x \in \{0, 1\}, \mathbb{S}. \end{cases} \quad (5.89)$$

where \mathbb{S} is the collection of all feasible partitioning of the followers.

As for the lower level problem, by replacing $y_j = 1 - \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S)$, it is equivalent to the following bi-linear optimization problem:

LP:

$$\min_{x,v} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} (v_i(S) - \sum_{j \in V} V_j \delta_{jS}) x_i(S) + \sum_{j \in V} V_j \quad (5.90)$$

$$s.t. \begin{cases} 0 \leq v_i(S) \leq \sum_{j \in S} V_j & \forall i \in N, \end{cases} \quad (5.91)$$

$$\begin{cases} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) \leq 1 & \forall j \in V, \end{cases} \quad (5.92)$$

$$\begin{cases} \sum_{S \in \mathcal{F}_i} x_i(S) \leq 1 & \forall i \in N, \end{cases} \quad (5.93)$$

$$\begin{cases} x_i(S) \in \{0, 1\} & \forall i \in N, \forall S \in \mathcal{F}_i. \end{cases} \quad (5.94)$$

This problem can be formulated as a mixed integer bilevel bilinear programs.

5.3.3.1 Linearization procedure for UP and LP

Notice that both **UP** and **LP** have the following form

$$\min_{v,x} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} x_i(S) D_i(v) \quad (5.95)$$

$$s.t. \begin{cases} \mathbb{L}(x, v) & \forall i \in N, \end{cases} \quad (5.96)$$

$$\begin{cases} x_i \in \{0, 1\}. \end{cases} \quad (5.97)$$

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where $D_i(v)$ is a linear function of v ; $\mathbb{L}(x, v)$ is a set of linear constraints.

Since the variable $v_i(S)$ is bounded by the market price, then the function $D_i(v)$ for **UP** and **LP** must lie between certain bounds:

$$\underline{D_i^{UP}} \leq D_i^{UP} \leq \overline{D_i^{UP}}$$

and

$$\underline{D_i^{LP}} \leq D_i^{LP} \leq \overline{D_i^{LP}}$$

By applying the development in [Oral & Kettani \(1992\)](#), the **UP** can be written as:

$$\min_{x,v} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \underline{D_i^{UP}} x_i(S) + \xi_i(S) \quad (5.98)$$

$$s.t. \begin{cases} \xi_i(S) \geq D_i^{UP}(v) - \underline{D_i^{UP}} x_i(S) - \overline{D_i^{UP}}(1 - x_i(S)) & \forall i \in N, S \in \mathcal{F}_i \quad (5.99) \\ 0 \leq v_i(S) \leq \sum_{j \in S} V_i(j) & \forall i \in N, \quad (5.100) \\ x \in \{0, 1\}, \quad \mathbb{S}, & (5.101) \\ \xi_i(S) \geq 0 & \forall i \in N, S \in \mathcal{F}_i. \quad (5.102) \end{cases}$$

In the similar way, the **LP** is equivalent to the following problem:

$$\min_{x,v} \sum_{i \in N} \sum_{S \in \mathcal{F}_i} D_i^{LP}(v) - \overline{D_i^{LP}}(1 - x_i(S) + \xi_i(S)) \quad (5.103)$$

$$s.t. \begin{cases} \xi_i(S) \geq -D_i^{LP}(v) + \underline{D_i^{LP}} x_i - \overline{D_i^{LP}}(1 - x_i) & \forall i \in N, S \in \mathcal{F}_i, \quad (5.104) \\ 0 \leq v_i(S) \leq \sum_{j \in S} V_i(j) & \forall i \in N, \quad (5.105) \\ \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) \leq 1 & \forall j \in V, \quad (5.106) \\ \sum_{S \in \mathcal{F}_i} x_i(S) \leq 1 & \forall i \in N, \quad (5.107) \\ x \in \{0, 1\}, & (5.108) \\ \xi_i(S) \geq 0 & \forall i \in N, S \in \mathcal{F}_i. \quad (5.109) \end{cases}$$

Finally, the general case bilevel problem is equivalent to a mixed integer bilevel programming with binary variable. It is solvable by the algorithms developed in

(Fischetti *et al.*, 2017) and (Tahernejad *et al.*, 2016).

5.4 Risk cost in shipper's objective function

In the more complex real world applications, not only the price is evaluated in the carrier selection, but also the quality of service. **Allianz Global Corporate & Specialty** has provided a report to measure the carriers' performance periodically*. Indeed, before a shipper can move its goods to market, special care must be taken to carefully scrutinize and select an appropriate method of transportation and a reliable carrier, or transportation provider, to move the goods quickly, safely, and at the best rate with minimal risk of damage, loss or theft.

In the report, more than thirty criteria are considered to evaluate the carriers' service level and how they can affect the shippers' choice. These criteria, including but not limited to *Organizational structure, Professional reputation, Present customer contacts/references, Financial stability, Carrier's costing/financing system, Billing cycles, Quality of carrier and staff, Operating philosophy, Workforce, Geographical coverage, Communications capability, On-time performance and target, Fleet size, Intermodal linkages/partners, Use of owner-operators and/or subcontractors, Cargo service, Fleet condition and maintenance, Cargo equipment inspection frequency and procedures, Experience in hauling cargo similar to yours, High value cargo handling and transport, Cargo security devices, Cargo information security, Cargo tracking, Routing, Pre-employment, Training, Discipline, Cargo inventory, Loss/damage notification, Insurance Coverage, Limits of liability, Loss and damage experience, Claims handling philosophy and standards, Monitoring and Control.*

In the transportation procurement literature, [Othmane *et al.* \(2014a,b\)](#); [Rekik & Mellouli \(2012\)](#) considered reputation - based WDP problem in transportation CAs. The objective for shippers is to find a trade off between transport costs and the quality of service during operations. In their work, the carriers' reputation represents the aggregated service level. It differs from carrier to carrier, and also differs from shipper to shipper. In the auction process, the reputation is translated into unexpected hidden cost representing the possible additional cost/loss

*<https://www.agcs.allianz.com/insights/white-papers-and-case-studies/carrier-selection-criteria/>

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in shippers' carrier selection process. The shipper may develop numerical ratings for each carrier by weighting each criteria depending on their importance. By doing so, it is able to build an incentive market in which carriers are forced to improve their performance as each of them will be vying to increase their market share.

In this section, a risk cost added to the shipper's objective function to represent the loss it may occur when considering carriers' service level. For a given bundle S and a given carrier i , the risk cost is defined as $R_i(S)$. The single-leader single-follower bilevel formulation is given by,

$$\max_v \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \left(\sum_{j \in S} v_i(j) - \text{OperC}_i(S) \right) x_i(S) - z_i \overline{\text{OperC}_i(\mathcal{F}_i)} \quad (5.110)$$

$$s.t. \left\{ \begin{array}{l} \sum_{S \in \mathcal{F}_i} x_i(S) + z_i = 1 \quad \forall i \in N, \quad (5.111) \\ \min_x \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \left(\sum_{j \in S} v_i(j) + R_i(S) \right) x_i(S) + \sum_{j \in V} V_j y_j \quad (5.112) \\ \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) \leq 1 \quad \forall j \in V, \quad (5.113) \\ \sum_{S \in \mathcal{F}_i} x_i(S) \leq 1 \quad \forall i \in N, \quad (5.114) \\ \sum_{i \in N} \sum_{S \in \mathcal{F}_i} \delta_{jS} x_i(S) + y_j = 1 \quad \forall j \in V, \quad (5.115) \\ x_i(S), y_j, z_i \in \{0, 1\} \quad \forall i \in N, \forall S \in \mathcal{F}_i, \forall j \in V. \quad (5.116) \end{array} \right.$$

Remark 5.8 *What have changed?*

- *Even in the optimistic case, due to the risk cost occurred in the carrier selection, the carriers are forced to propose price lower than the spot market price;*
- *The risk cost is an information that the shipper may not share with the carriers. The updating prices strategy for carriers is unclear. If the risk cost is hidden from carriers, the lower level problem seems like a black box optimization problem;*

- *Price on bundles? Or on individual lanes? If carriers simply change their lane prices when they want to get certain bundles, the other unwanted bundles may have attractive prices as. As the risk is related with bundles and with carriers, the lane in different bundles may reveal different values.*

5.5 Experimental Results

In this section, we provide the numerical test results obtained from individual lane pricing and bundle pricing, different cases are evaluated and discussed. In addition, we also study the bundle pricing strategy with informed carriers.

5.5.1 Individual lane pricing

We define a cost matrix for shipper when generating bundle allocations among carriers, in which carriers are listed in lines and the bundle costs are presented in columns, each matrix coordinate is the given price and its risk cost. All bundles are supposed can be allocated to all carriers, when one carrier can not serve one bundle, he set the infinity price. A random risk cost is associated with each bundle. The cost of a bundle and of a carrier is the summation of the price proposed by this carrier and the risk cost. The objective of the shipper is to find a conflict-free allocation while the total cost is minimized.

As for the carriers, we define a profit matrix in which carriers are listed in lines and the bundle profits are presented in columns, each matrix coordinate is the given price and its operating cost. The profit of a bundle for a carrier is the summation of the profit minus the cost to cover this bundle, an empty set is given to represent the case a carrier is assigned with nothing. The objective of the carriers is to adapt their pricing strategies in order to maximize their total revenue.

Hereafter, the solution of a final pricing-allocation in the matrix are marked in red color.

The goal of the bilevel model is to find a compromised solution favors both the shipper and the carriers. The strategy to find the optimal solution is iteratively reducing the price of each lane for each carrier until the price is accepted by the auctioneer.

**5. SINGLE-LEADER SINGLE-FOLLOWER
PRICING-ALLOCATION BILEVEL MODEL IN CAS FOR FULL
TRUCKLOAD TRANSPORTATION PROCUREMENT**

5.5.1.1 Case 1

The network is depicted in Figure 5.4, $C1, C2$ are carriers, node $C1, C2$ are carriers' origin/destination from left to right; each node R represents a lane request, arrow lines are truck movement from request to request; requests in same color are feasible bundles. With carrier $C1, C2$ as line 1, 2, and bundle $(R1, R2), (R3, R2), (R3)$ as column 1, 2, 3, the cost matrix for shipper and the profit matrix for carriers is as follows if initially give the market price,

$$\begin{array}{ccc}
 & (R1, R2) & (R3, R2) & (R3) \\
 C1 \left[\begin{array}{ccc} 9, 2 & +\infty & +\infty \\ +\infty & 12, 1 & 8, 1 \end{array} \right] & & & \\
 C2 \left[\begin{array}{ccc} 9, -3 & -\infty & -\infty \\ -\infty & 12, -6 & 8, -3 \end{array} \right] & & & \\
 & (R1, R2) & (R3, R2) & (R3) & \emptyset \\
 & 9, -3 & -\infty & -\infty & -6 \\
 & -\infty & 12, -6 & 8, -3 & -4
 \end{array}$$

If the shipper receives the market price from the carriers, due to the risk cost,

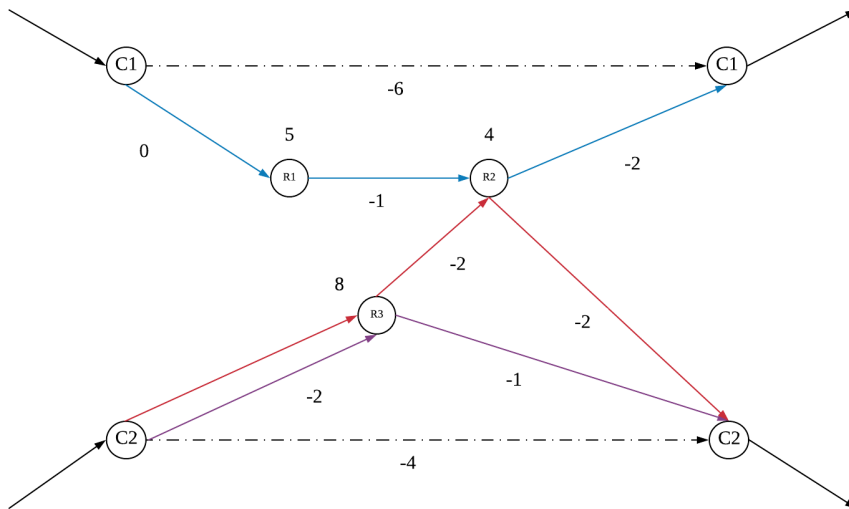


Figure 5.4: Example 1 of the single-leader single-follower pricing-allocation bilevel model.

5.5 Experimental Results

no bundle will assign to carriers, all bundles go to spot market. The carriers will operate as the empty set cost with -10. As shipper only assign a bundle to a carrier when the cost of this bundle is lower than the market price.

The optimal solution is given by

$$\begin{array}{c}
 \begin{array}{ccc}
 (R1, R2) & (R3, R2) & (R3) \\
 C1 \left[\begin{array}{ccc}
 7, 2 & +\infty & +\infty \\
 +\infty & 11, 1 & 7, 1
 \end{array} \right] & & \\
 C2 & &
 \end{array}
 &
 \begin{array}{c}
 \begin{array}{cccc}
 (R1, R2) & (R3, R2) & (R3) & \emptyset \\
 C1 \left[\begin{array}{cccc}
 7, -3 & -\infty & -\infty & -6 \\
 -\infty & 11, -6 & 7, -3 & -4
 \end{array} \right] & & &
 \end{array}
 \end{array}
 \end{array}$$

with

$$\begin{aligned}
 v_{C1}(R1) &= 3, & v_{C1}(R2) &= 4, & v_{C1}(R3) &= 8 \\
 v_{C2}(R1) &= 5, & v_{C2}(R2) &= 4, & v_{C2}(R3) &= 7
 \end{aligned}$$

The total gain of carriers are 8 and the total cost of shipper is 17. These values are the same to the case where the requests are assigned to the spot market.

Remark 5.9 • *As the best allocation for carriers consists in assigning to each carrier with exactly one bundle to avoid the empty set cost, carriers need to pre-decide the best allocation to maximize his profit. They determine prices to lead the shipper to define this best allocation. In the example, they decrease the price on R1, R3, and increase the price on R2;*

- *The risk cost is the factor to avoid the carriers to set the market price, there is no benefit improved for the shipper, the risk cost is a upper bound for carrier to set the price. The carrier must determine a lower price to win this bundle, that is, for a carrier i ,*

$$\sum_{j \in S} v_i(j) \leq \sum_{j \in S} V_j - R_i(S) \tag{5.117}$$

5.5.1.2 Case 2

We slightly change the Example 1 where C2 cover bundle (R3, R2) with risk cost 0. In this case, the cost matrix for shipper and the profit matrix for carriers will be as follows,

$$\begin{array}{c}
 \begin{array}{ccc}
 (R1, R2) & (R3, R2) & (R3) \\
 C1 \left[\begin{array}{ccc}
 9, 2 & +\infty & +\infty \\
 +\infty & 12, 0 & 8, 1
 \end{array} \right] & & \\
 C2 & &
 \end{array}
 &
 \begin{array}{c}
 \begin{array}{cccc}
 (R1, R2) & (R3, R2) & (R3) & \emptyset \\
 C1 \left[\begin{array}{cccc}
 9, -3 & -\infty & -\infty & -6 \\
 -\infty & 12, -6 & 8, -3 & -4
 \end{array} \right] & & &
 \end{array}
 \end{array}
 \end{array}$$

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Since there is no risk cost associated with an allocation for shipper to give request to spot market, if carriers define prices as in Case 1, bundle $(R3, R2)$ will be chosen. $C1$ will suffer an empty truck cost of -6. The total cost for carriers is -1 and the cost for shipper is unchanged. In fact, the optimal solution is

$$\begin{array}{c}
 C1 \\
 C2
 \end{array}
 \begin{array}{ccc}
 (R1, R2) & (R3, R2) & (R3) \\
 \left[\begin{array}{ccc}
 \mathbf{6, 2} & +\infty & +\infty \\
 +\infty & 11, 0 & \mathbf{7, 1}
 \end{array} \right]
 \end{array}
 \quad
 \begin{array}{c}
 C1 \\
 C2
 \end{array}
 \begin{array}{ccc}
 (R1, R2) & (R3, R2) & (R3) & \emptyset \\
 \left[\begin{array}{ccc}
 \mathbf{6, -3} & -\infty & -\infty & -6 \\
 -\infty & 11, -6 & \mathbf{7, -3} & -4
 \end{array} \right]
 \end{array}$$

with

$$\begin{aligned}
 v_{C1}(R1) &= 2, & v_{C1}(R2) &= 4, & v_{C1}(R3) &= 8 \\
 v_{C2}(R1) &= 5, & v_{C2}(R2) &= 4, & v_{C2}(R3) &= 7
 \end{aligned}$$

The total gain of carriers are 7 and the total cost of shipper is 16 which represents one unit saving compare with Case 1.

Remark 5.10 *The difference between Case 1 and 2 comes from the fact that prices are defined on individual requests not on bundles. Decreasing the price on $R3$, it results in decreasing the price on the bundle $(R3, R2)$. If we price on bundles, for example, when $C2$ descend the price on $(R3)$ with bundle price for $(R3, R2)$ staying the same, there will exist no saving for shipper anymore.*

5.5.2 Bundle pricing

As discussed in last section, pricing on individual lanes can not reveal their true values when they are in different bundles which have different risk cost. The best way of addressing this problem is to make bundle prices superadditive in the number of lanes. The fact that bidders' valuations satisfy this property is often a motivation for holding a combinatorial auction in the first place.

5.5.2.1 Case 3

In this section, we use the network depicted in Figure 5.5 and we consider bundle pricing strategy. $C1, C2$ are carriers, node $C1, C2$ are carriers' origin/destination from left to right; each node R represents a lane request, arrow lines are truck movement from request to request; requests in same color are feasible bundles.

5.5 Experimental Results

The bundle pricing corresponds to the general case of bilevel problem, it is a mixed integer bilevel programming with binary variables and solvable by the solver developed in [Tahernejad et al. \(2016\)](#).

We consider two risk form, the first is carrier based, which means a fixed risk cost is attached to a carrier regardless his bundle set information; the second is bundle based, which we give a concave risk cost function which depend on the bundles' size.

The cost of the carrier based risk is 1.5 and 1 for carrier $C1$ and $C2$. Initially with the market price given, the corresponding cost matrix for shipper and the profit matrix for carriers is as follows:

$$\begin{array}{l}
 C1 \begin{bmatrix} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) \\ 9, 1.5 & 17, 1.5 & +\infty & +\infty \\ +\infty & +\infty & 12, 1 & 8, 1 \end{bmatrix} \quad C1 \begin{bmatrix} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) & \emptyset \\ 9, -3 & 17, -4 & -\infty & -\infty & -6 \\ -\infty & -\infty & 12, -6 & 8, -3 & -4 \end{bmatrix} \\
 C2 \begin{bmatrix} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) \\ 9, 1.5 & 17, 1.5 & +\infty & +\infty \\ +\infty & +\infty & 12, 1 & 8, 1 \end{bmatrix} \quad C2 \begin{bmatrix} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) & \emptyset \\ 9, -3 & 17, -4 & -\infty & -\infty & -6 \\ -\infty & -\infty & 12, -6 & 8, -3 & -4 \end{bmatrix}
 \end{array}$$

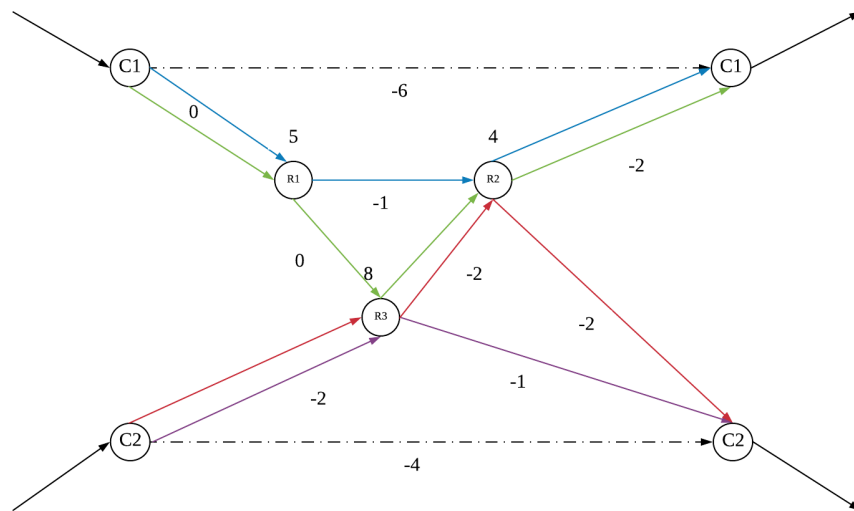


Figure 5.5: Example 2 of the single-leader single-follower pricing-allocation bilevel model.

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and its optimal solution given is:

$$\begin{array}{c}
 C1 \left[\begin{array}{cccc} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) \\ \mathbf{7, 1.5} & 17, 1.5 & +\infty & +\infty \\ C2 \left[\begin{array}{cccc} +\infty & +\infty & 12, 1 & \mathbf{7, 1} \end{array} \right]
 \end{array} \right] &
 C1 \left[\begin{array}{cccc} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) & \emptyset \\ \mathbf{7, -3} & 17, -4 & -\infty & -\infty & -6 \\ C2 \left[\begin{array}{cccc} -\infty & -\infty & 12, -6 & \mathbf{7, -3} & -4 \end{array} \right]
 \end{array} \right]
 \end{array}$$

The cost of bundle based risk is set 1, 1,3 and 1.5 if a bundle contain 1, 2 and 3 lanes. Initially with the market price proposed, the corresponding cost matrix for shipper and the profit matrix for carriers is as follows:

$$\begin{array}{c}
 C1 \left[\begin{array}{cccc} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) \\ 9, 1.3 & 17, 1.5 & +\infty & +\infty \\ C2 \left[\begin{array}{cccc} +\infty & +\infty & 12, 1.5 & 8, 1 \end{array} \right]
 \end{array} \right] &
 C1 \left[\begin{array}{cccc} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) & \emptyset \\ 9, -3 & 17, -4 & -\infty & -\infty & -6 \\ C2 \left[\begin{array}{cccc} -\infty & -\infty & 12, -6 & 8, -3 & -4 \end{array} \right]
 \end{array} \right]
 \end{array}$$

and its optimal solution given is:

$$\begin{array}{c}
 C1 \left[\begin{array}{cccc} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) \\ \mathbf{7, 1.3} & 17, 1.5 & +\infty & +\infty \\ C2 \left[\begin{array}{cccc} +\infty & +\infty & 12, 1.3 & \mathbf{7, 1} \end{array} \right]
 \end{array} \right] &
 C1 \left[\begin{array}{cccc} (R1, R2) & (R1, R3, R2) & (R3, R2) & (R3) & \emptyset \\ \mathbf{7, -3} & 17, -4 & -\infty & -\infty & -6 \\ C2 \left[\begin{array}{cccc} -\infty & -\infty & 12, -6 & \mathbf{7, -3} & -4 \end{array} \right]
 \end{array} \right]
 \end{array}$$

In results from the experiments, both of the cases can generate a cost saving for shipper when the risk cost is not integer. For example, for carrier based risk, the saving for shipper is 0.5 unit; as for bundle based risk, the saving is 0.7 unit.

5.5.2.2 Case 4

In this section, we enlarge the data set and add to the previous example with 6 requests, each carrier has 4 bundles that he may serve. The market price is defined as 2, 2, 1, 2, 2, 1 for request 1 to 6 respectively.

In the first test, the bundle profile for the carriers and the final allocation and prices (marked in red) without risk at the lower level are given in Table 5.3. The time node is 0, nodes fully or partially processed are 860 and 56, nodes branched is 615, tree depth is 23, search CPU time is 0.97s, feasibility check used 0.6380s.

We next define the risk at the lower level with 20% and 10% of the Market Price for carrier 1 and 2. The optimal solution and the final allocation is given in Table 5.4. In this test, time node is 1185, nodes fully or partially processed are 545378 and 1947, nodes branched is 273662, tree depth is 30, search CPU time is 1283.65s, feasibility check used 845.0343s.

5.5 Experimental Results

Carrier	Bundle	Market Price	Operation cost	Optimal solution
1	(1,2,3)	5	-2	5
	(2,4)	4	-1	4
	(4,5)	4	-1	4
	(3,4)	3	-1	3
2	(1,3,6)	4	-1	4
	(2,5)	4	-2	4
	(3,4)	3	-1	3
	(1,5)	4	-2	4

Table 5.3: Centralized bundle pricing without risk at the lower level.

Carrier	Bundle	Market Price	Operation cost	Optimal solution
1	(1,2,3)	5	-2	5
	(2,4)	4	-1	3
	(4,5)	4	-1	4
	(3,4)	3	-1	3
2	(1,3,6)	4	-1	3
	(2,5)	4	-2	3
	(3,4)	3	-1	3
	(1,5)	4	-2	4

Table 5.4: Centralized bundle pricing with risk at the lower level.

Again, without risk at the lower level, the carriers are proposing highest allowed prices, i.e. the market price. With the risk at the lower level, the cost saving is again comes from the fact that the carriers can only set integer prices.

Observe that, introducing risk at the lower level can largely increase the searching effort. Indeed, the computational time can increase up to 2128.6843s, 1324 times of the computation time comparing without risk at the lower level.

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5.5.3 Bundle pricing with informed carriers

In this section, we intend to check how informed carriers can benefit from the mechanism that we have developed. As discussed in Remark 5.10, there is no saving for shipper if we consider no risk evaluated on carriers, thus in the following tests, we will consider the case without risk cost and only discuss the infection of introducing the informed carriers.

We use the same data set as in Chapter 4. The case tested used a compressed instance from C101 with 50 nodes, from the knowledge of previous sections, the computational time is relatively large if we consider the origin data. We only consider 20% of the C101 request nodes, which have 14 request nodes in total.

We consider three informed carriers and one traditional carrier, each informed carrier is associated with a different origin-destination node pair, and the traditional carrier departs and goes back to node 0. The bundle pool is computed by the algorithm defined in Chapter 4 with same time limitation.

We give the 4 carriers with his origin-destination node pair as follows:

- 6-27: informed carrier 1 with 8 bundles and with largest bundle size 3;
- 5-42: informed carrier 2 with 9 bundles and with largest bundle size 3;
- 33-6: informed carrier 3 with 14 bundles and with largest bundle size 3;
- 0-0: traditional carrier with 2 bundles and with largest bundle size 3.

Without risk cost at the lower level, four tests are performed. In each test, three carriers are defined to evaluate the affection of informed carriers. The time limit is set as 1 hour,

- 3 different informed carriers (6-27, 5-42, 33-6): The origin profit for the upper level without lower level is 105 and the final profit is 35 with totally 7 covered nodes;
- 2 informed carrier (6-27, 5-42) and 1 traditional carrier: the origin profit for the upper level without lower level is 75 and the final profit is 2 with totally 5 covered nodes and traditional carrier is assigned with nothing;
- 1 informed carrier (6-27) and 2 traditional carriers: the origin profit for the upper level without lower level is 45 and the final profit is 15 with totally 5 covered nodes and 1 traditional carrier is assigned with nothing.

- 3 traditional carriers: the origin profit for the upper level without lower level is 19 and the final profit is -69 with totally 3 covered nodes and 2 traditional carrier is assigned with nothing.

Remark 5.11 • *Without the lower level, i.e. the carriers do the allocation themselves, it equivalent to the case of multiple vehicle routing problems, the profit is decreasing by decreasing the number of informed carriers, the profits are 105, 75, 45, 19 with 3, 2, 1, 0 informed carriers;*

- *With the allocation of the lower level, the profit is decreasing by decreasing the number of informed carriers, the profits are 35, 2, 15, -69 with 3, 2, 1, 0 informed carriers, note that the final profit is calculated by the time limit of 1 hour, it is not the optimal solution;*
- *The total number of requests is decreasing by decreasing the number of informed carriers, the number of requests covered are 7, 5, 5, 3 with 3, 2, 1, 0 informed carriers.*

5.6 Conclusions

We describe a bilevel model in combinatorial auctions to express the interaction between the BGP and the WDP, the problem aims to identify an optimal solution in which the carriers' decisions are taken considering the shipper reaction.

The contribution of this chapter are: 1, we are the first to merge the BGP and the WDP as the centralized pricing-allocation bilevel model; 2, we are able to solve the pricing-allocation problem exactly by replacing the lower level problem by its primal-dual optimality conditions in both the 1-to-1 pricing-allocation case and the general bilevel case; 3, we introduce and define the risk cost in shipper's objective function.

In the experimental results, we show that:

- In both individual and bundle pricing, risk cost can generate saving for shipper if carriers only can set integer prices;
- Introducing risk cost at the lower level can largely increase the searching effort of our algorithm;

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- The traditional carrier has the obvious disadvantage to cover bundles both in qualities and in quantities comparing with informed carrier.

Nevertheless, the formulations developed and the algorithm used can only solve very small size instances, and the computational time is already long, thus more efficient heuristics need to be developed to solve the same problem.

Chapter 6

Multi-leader Single-follower Pricing-Allocation Bilevel Model in CAs for Full Truckload Transportation Procurement

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Observe that, for the formulation presented in previous Chapter, carriers are cooperating with each other to achieve the highest total profit, which does not reveal the truth that carriers could adjust their pricing strategies themselves to

6. MULTI-LEADER SINGLE-FOLLOWER PRICING-ALLOCATION BILEVEL MODEL IN CAS FOR FULL TRUCKLOAD TRANSPORTATION PROCUREMENT

get more profit for their own. Indeed, cooperating among carriers is a strong assumption which will lead to a strong centralization at the carriers' level, thus the single-leader single-follower pricing-allocation bilevel model can be seen as with only one carrier but with different truck resources, it eventually falls into a resource planning problem at the upper level. And this is also why carriers in most solutions are proposing highest market prices and there is less saving for the shipper.

In real world applications, in order to gain more market share, to keep up in the development of the new technology, to have higher standards for competence and to sustain the current pace of growth, the carriers at the upper level are under pressure and generally selfish/distributed. They can build and enlarge their own logistic network and operate individually or cooperate very closely to achieve global and self profit goals. In other words, carriers compete with each other, to avoid congestion and minimize their travel time, and on public transport, to purchase the cheapest tickets or maximize the comfort of their journey. Moreover, carriers compete also on price, quantity, quality and other features to attract customers.

In literature, several papers are targeting less-than-truckload carrier collaboration as it allows more flexibility to exchange, reallocate lanes among different carriers in a complex logistic network and in a dynamic environment (Berger & Bierwirth, 2010; Hernández & Peeta, 2014; Hernández *et al.*, 2011; Liu *et al.*, 2010a; Nadarajah & Bookbinder, 2013). Truckload carrier collaboration can be included in the less-than-truckload researches when carriers can reduce back-haul or empty movement cost through lane exchange (Liu *et al.*, 2010b; Özener *et al.*, 2011). Other papers discuss the profit sharing problem by doing the collaboration (Dai & Chen, 2012; Krajewska *et al.*, 2008; Liu *et al.*, 2010a). Finally considering carrier collaboration under auction concept, works can be found in Dai & Chen (2011); Dai *et al.* (2014); Gansterer & Hartl (2016); Lai *et al.* (2017); Song & Regan (2003b); Xu *et al.* (2016).

The discipline that studies competition among groups of decision-makers where individual choices can jointly determine the final outcome is known as game theory. Two types of non-cooperative games are involved and discussed in this chapter, namely the Nash game and the Stackelberg game. In Nash game (Nash, 1951), the decision makers who have equal status and they are making decisions

6.1 Multi-leader single-follower bilevel formulation

at the same time. Each player can affect their competitors' decisions by changing their strategy unilaterally, and the outcome for each of them depends on the decisions of the others. Under this setting, Nash equilibrium solution is a state in which no player can improve his outcome by unilaterally changing his decision. Stackelberg game (Stackelberg *et al.*, 1952) features two players, identified as leader and follower, both trying to optimize their own objective function, the leader take into account the follower's reaction when optimizing its decisions.

In this Chapter, we consider a pure competitive environment to express the relationship among the carriers at the upper level. The competitive feature among carriers draws the Nash game at the upper level. Each carrier's decision not only is determined by the follower's response but is also influenced by other carriers strategies. Multi-leader/carriers single-follower/shipper bilevel model is employed to fully express the complex relationship among all players.

6.1 Multi-leader single-follower bilevel formulation

In this section, we introduce the carrier interaction and carrier-shipper interaction with the same notations as in Chapter 5 and give the multi-leader single-follower bilevel formulation.

6.1.1 Carrier interaction

Let v_i be the vector price proposed by carrier i over all the transportation requests. The alternative offers proposed by the other carriers other than i , is denoted by*

$$\mathbf{v}_{-i} = (\mathbf{v}_1, \dots, \mathbf{v}_{i-1}, \mathbf{v}_{i+1}, \dots, \mathbf{v}_n), \quad (6.1)$$

it interacts with the choice \mathbf{v}_i of carrier i through the choice of the lower level - shipper. If an alternative carrier proposes a very attractive offer (i.e., with lower prices), the cost at the lower level should be reduced.

Setting a proper offer against the other carriers' offers (i.e. \mathbf{v}_{-i}) to gain more profit is challenging task for each carrier, then in competition.

*Standard notation in game theory to define the strategy of all the players but one, i.e. his opponents.

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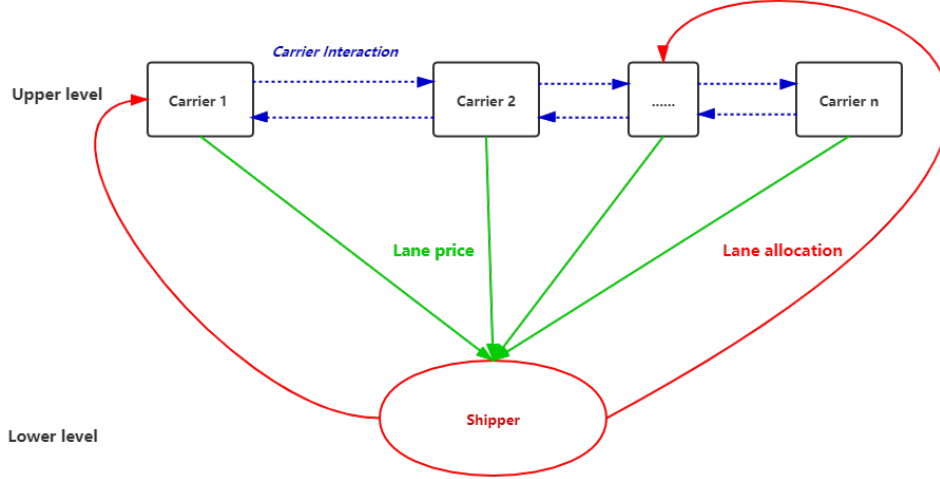


Figure 6.1: Illustration of the proposed model for the competition between carriers and shipper.

6.1.2 Carrier-shipper intersection

The relation between carriers and shipper can be modeled as a bilevel competition game named Stackelberg multiple-leader single-follower game. Consider the network depicted in Figure 6.1, carriers at the upper level propose individual offers - in a competitive manner - to the shipper, shipper react to the prices by allocating the lanes to the carriers.

6.1.3 Multi-leader single-follower bilevel formulation

Given $\mathcal{X}_i(\mathbf{v}_i, \mathbf{v}_{-i})$ the solution of the lower level problem - the shipper's allocation problem - under the **competition** between carriers. The multi-leader single-follower bilevel formulation for each $i \in N$ is given by,

$$\Pi_i(\mathbf{v}_i, \mathbf{v}_{-i}) = \max_{\substack{v_i, \\ x_i \in \mathcal{X}_i(\mathbf{v}_i, \mathbf{v}_{-i})}} \sum_{S \in F_i} (v_i(S) - \text{OperC}_i(S)) x_i(S) - z_i \overline{\text{OperC}_i(\mathcal{F}_i)} \quad (6.2)$$

where Π_i is the utility function defined for carrier i when he set price v_i respecting the other carrier's offer v_{-i} .

The other carrier's offers \mathbf{v}_{-i} are not represented in each carrier's objective function but will interact with the shipper's decision at the lower level as $\mathcal{X}_i(\mathbf{v}_i, \mathbf{v}_{-i})$.

For fixed \mathbf{v}_{-i} , each carrier i has to solve a single-leader single-follower bilevel programming problem. The final solution \mathbf{v}_i leads to a Nash Equilibrium among all carriers, in other words, no carrier can improve their profit by changing only their own pricing strategy.

6.2 Solution approach

In this section, we propose an iterative approach to obtain the Nash equilibrium between carriers by using a standard game theoretical dynamics named best response dynamics.

6.2.1 Best response

Game theory offers us a way to approach the solution for our problem with an iterative procedure, which is [best response dynamics](#). In evolutionary game theory ([Fudenberg & Tirole, 1991](#)). Best response dynamics represents a class of strategy updating rules, where players strategies in the next iteration are determined by their best responses of current iteration.

To solve the problem of our defined multi-leader single-follower model, the other carriers' offers $\mathbf{v}_{-i,r}$ are fixed at round r . The adaptation dynamics of the next-round offer $r + 1$ for carrier i is

$$\mathbf{v}_{i,r+1} \in \arg \max_{\mathbf{v}_i} \Pi_i(\mathbf{v}_i, \mathbf{v}_{-i,r}). \quad (6.3)$$

6.2.1.1 1-to-1 pricing-allocation

In this section, we define the solution algorithm for the 1-to-1 pricing-allocation mentioned in section [5.3.2](#) under the multi-leader single-follower setting. The bilevel problem can be then reformulated as a single-level problem. Each carrier i need to solve the problem as follows,

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$$\Pi_i(\mathbf{v}_i, \mathbf{v}_{-i}) = \max_{x_i \in \mathcal{X}_i(\mathbf{v}_i, \mathbf{v}_{-i})} \sum_{j=1}^m (v_i(j) - \text{OperC}_i(j)) x_i(j) - \sum_{j=1}^m \overline{\text{OperC}_i(\mathcal{F}_i)} x_i(m+j) \quad (6.4)$$

$$s.t. \left\{ \begin{array}{l} \min_x \sum_{j=1}^m \sum_{i=1}^n v_i(j) x_i(j) + \sum_{j=1}^m \sum_{i=1}^n V_j x_{n+i}(j) \quad (6.5) \\ \sum_{i=1}^{2n} x_i(j) = 1 \quad \forall j \in \{1, \dots, 2m\}, \quad (6.6) \\ \sum_{j=1}^{2m} x_i(j) = 1 \quad \forall i \in \{1, \dots, 2n\}, \quad (6.7) \\ x_i(j) \geq 0 \quad \forall i \in \{1, \dots, 2n\}, j \in \{1, \dots, 2m\}. \quad (6.8) \end{array} \right.$$

The primal-dual reformulation can be written again as same as in Section 5.3.2.

According to the reformulation defined in Section 5.3.2, in the best response dynamics, for each round r , carrier i is able to compute his offer $v_{i,r}$ respecting the other carriers offers $v_{-i,r-1}$ by solving a single-level problem. Iteratively, the best response dynamics converges to a equilibrium solution for all carriers.

6.2.1.2 Bundle-to-carrier pricing-allocation

In this section, we define an algorithm to solve the bundles to carriers - we refer it as bundle-to-carrier pricing-allocation problem depicted in Figure 6.2.

In this problem, the lower level problem can not be easily replaced by its optimality conditions, making it more difficult to be solved by any exact algorithm. Nevertheless, if the price is the only factor affecting the shipper's decision, the best strategies for carriers to win a conflict lane is to reduce the price. Thus, by decreasing prices at each round for each carrier, we are able to find a stable solution.

Now we define $\mathcal{F}_{i,j}$ the set of bundles containing request j for carrier i , the problem is solved by the Algorithm 3.

Two stopping criteria can be considered in the Best Response technique,

- When a bundle is a subset of another bundle, this bundle profit must be lower than the other bundle, otherwise, the carrier will choose the smaller

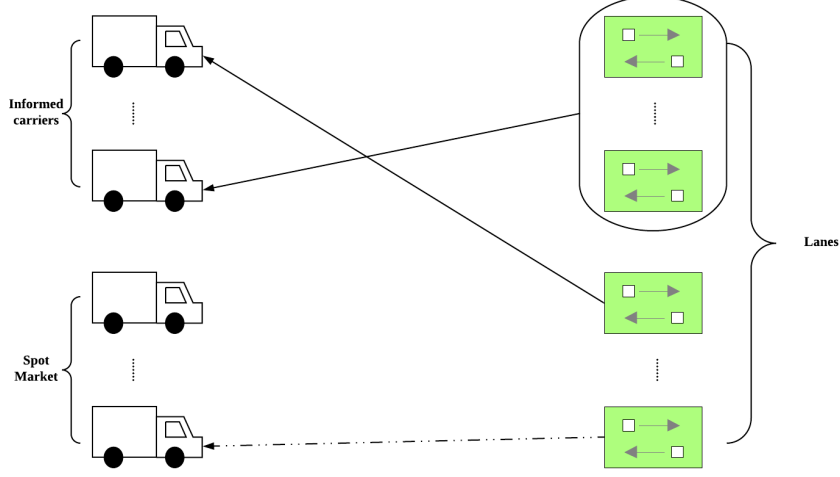


Figure 6.2: Bundle-to-carrier pricing-allocation

bundle and still keep the same profit. This leads us to define a lower bound for bundle pricing. For a carrier i ,

$$v_i(S) - \text{OperC}_i(S) > v_i(S') - \text{OperC}_i(S') \quad \forall S' \subset S.$$

Moreover, in the special case when carrier i is not covering any bundle, we have,

$$v_i(S) - \text{OperC}_i(S) > -\overline{\text{OperC}_i(\mathcal{F}_i)} \quad \forall S \subset \mathcal{F}_i$$

This inequality implies that negative price is acceptable as soon as the cost with this negative price is lower than the empty movement cost.

- Since carriers are reducing the prices of the conflicting lanes round by round, there will be a situation such that, in next round, a lot of carriers will choose not to covering any bundle. The uncovered lanes will be assigned to the spot market with highest prices, leading to increase cost for the shipper. Thus the shipper has to prevent this situation and stop the iteration at the right point, that is, the shipper's cost at next round $r + 1$ is

$$C_{r+1} > C_r. \tag{6.9}$$

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Algorithm 3 Bundle price evolution through Best Response

```

1: r=0: set  $v_i(j) = V(j), \forall i \in N, j \in V$ ;
2: for  $j \in V$  do
3:   for  $i \in N$  do
4:     while  $\mathcal{F}_{i,j} \neq \emptyset$  and  $\mathcal{F}_{i',j} \neq \emptyset, \forall i \neq i'$  do
5:        $v_i(j) = v_i(j) - 1$ ;
6:       dominate the unprofitable bundles and update the set  $\mathcal{F}_{i,j}$ ;
7:       solve the WDP problem for shipper and the shipper's cost is  $C_k$ ;
8:       if  $C_r > C_{r-1}$  then
9:         Stop;
10:      else
11:        if there is no conflict interest among carriers for  $j$  then
12:           $V = V \setminus j$ ;
13:        else
14:           $r = r + 1$ ;

```

6.3 Experimental results

Three instances are generated for the Bundle-to-Carrier Pricing-Allocation model. They are illustrated in Figure 6.3 - 6.5. In these instances, Requests $R1$, $R2$ and $R3$ are lanes with highest market prices. Arcs link the carriers and the requests with its transportation cost. Carrier $C1$ and $C2$ are moving from left to right, they either pass the colored bundle path or pass the dashed lines as a direct path.

Strategy to get the final solution: if there is a conflict of interest for two carriers on a request, they will lower their prices for their bundles iteratively until one of the carrier give up on his bundle in cause of no profit.

6.3.1 Instance 1

Bundle sets for the carriers:

- $C1: \{(R1, R2)\}$
- $C2: \{(R3, R2), (R3)\}$

Evaluation of the solution:

In this instance, requests $R1$ and $R3$ are not conflicting within two carriers, carrier $C1$ and carrier $C2$ will always set the highest prices for these two requests.

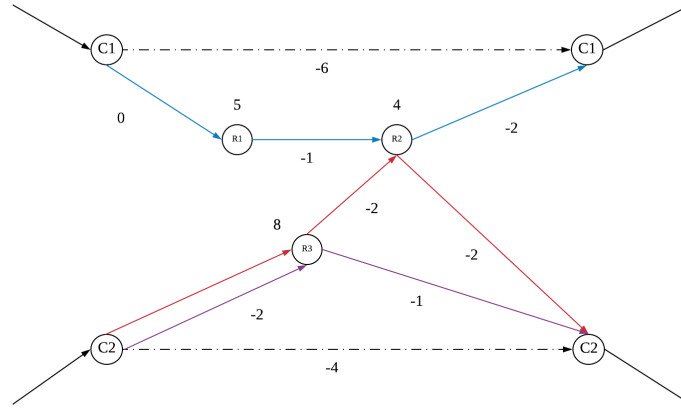


Figure 6.3: Instance 1 of the multi-leader single-follower bundle pricing model.

Request $R2$ is a conflict of interest for two carriers, carrier $C1$ decrease his bundle $\{(R1, R2)\}$ price as long as this bundle can give him a profit that is higher than -6 which is transportation cost for not covering any bundle. Carrier $C2$ will lower his bundle $\{(R3, R2)\}$ price as long as request $R2$ has no interest for him. In other words, passing bundle $\{(R3, R2)\}$ has equal or less profit than only passing bundle $\{(R3)\}$. As shown in Table 6.1, for each round, the new prices and profits are obtained by adjusting the price on request $R2$.

Round	Price			Profit		
	R1	R2	R3	(R1,R2)	(R3,R2)	(R3)
1	5	4	8	6	6	5
2	5	3	8	5	5	5

Table 6.1: Bundle pricing through best response for instance 1.

Solutions of the instance:

- $C1$: $\{(R1, R2)\}$ with bundle price $(5+3=)$ 8 and profit $(8-1-2=)$ 5
- $C2$: $\{(R3)\}$ with bundle price 8 and profit $(8-2-1=)$ 5

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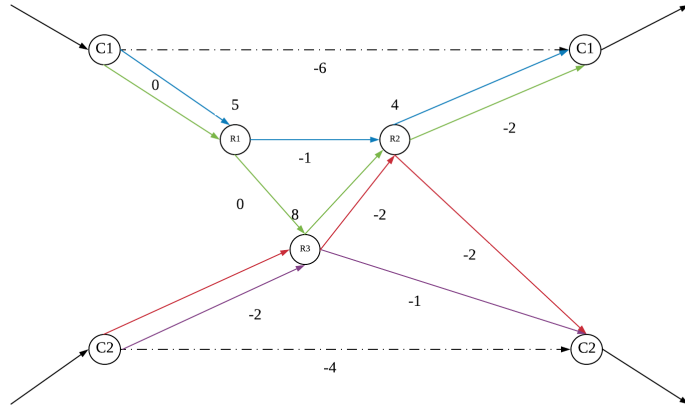


Figure 6.4: Instance 2 of the multi-leader single-follower bundle pricing model.

- Shipper: cost with 16

6.3.2 Instance 2

Bundle sets for the carriers:

- C1: $\{(R1, R2), (R1, R2, R3)\}$
- C2: $\{(R3, R2), (R3)\}$

Evaluation of the solution: In this instance, request $R2$, $R3$ are conflicts of interest for both carriers, price decrease on both $R2$ and $R3$. As shown in Table 6.2, from round 1 to 2, the price are decreasing on request $R2$ until there is no interest for carrier $C2$ to pass the bundle $(R3, R2)$; from round 3 to 9, the price are decreasing on request $R3$ until there is no interest for carrier $C1$ to pass the bundle $(R1, R3, R2)$.

Solutions of the instance:

- C1: $\{(R1, R2)\}$ with bundle price $(5+3=)$ 8 and profit $(8-1-2=)$ 5
- C2: $\{(R3)\}$ with bundle price 1 and cost $(1-2-1=)$ -2

6.3 Experimental results

Round	Price			Profit			
	R1	R2	R3	(R1,R2)	(R1,R3,R2)	(R3,R2)	(R3)
1	5	4	8	6	13	6	5
2	5	3	8	5	12	5	5
3	5	3	7	5	11	-	4
4	5	3	6	5	10	-	3
5	5	3	5	5	9	-	2
6	5	3	4	5	8	-	1
7	5	3	3	5	7	-	0
8	5	3	2	5	6	-	-1
9	5	3	1	5	5	-	-2

Table 6.2: Bundle pricing through best response for instance 2.

- Shipper: cost with 9

6.3.3 Instance 3

Bundle sets for the carriers:

- C1: $\{(R1, R2), (R1, R2, R3)\}$
- C2: $\{(R3, R2), (R3)\}$

Evaluation of the solution: In this instance, request $R2$, $R3$ are still conflicts of interest for both carriers, price decrease on both $R2$ and $R3$, but we change the market price at $R3$ as 4, the cost from $R3$ to carrier 2's destination is changed as -2 and the cost from $R3$ to $R2$ is changed to 0. As shown in Table 6.3, from round 1 to 5, the price is decreasing on request $R2$ until there is no interest for carrier $C2$ to pass the bundle $(R3, R2)$; from round 6 to 9, the price is decreasing on request $R3$ until there is no interest for carrier $C2$ to pass any bundle.

Solutions of the instance:

- C1: $\{(R1, R2, R3)\}$ with bundle price $(5+0+0=)$ 5 and profit $(5-2=)$ 3
- C2: takes no bundle

6. MULTI-LEADER SINGLE-FOLLOWER PRICING-ALLOCATION BILEVEL MODEL IN CAS FOR FULL TRUCKLOAD TRANSPORTATION PROCUREMENT

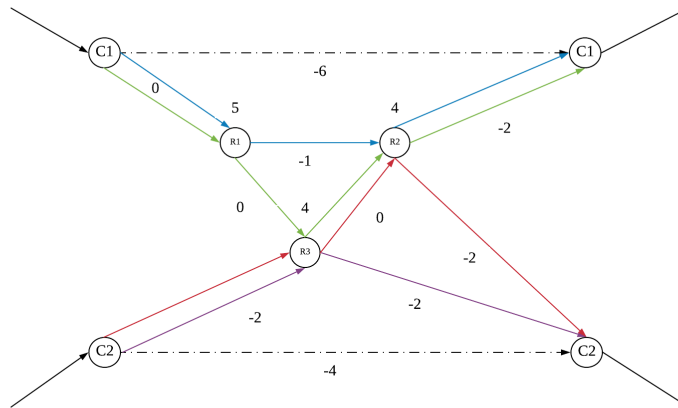


Figure 6.5: Instance 3 of the multi-leader single-follower bundle pricing model.

Round	Price			Profit			
	R1	R2	R3	(R1,R2)	(R1,R3,R2)	(R3,R2)	(R3)
1	5	4	4	6	11	4	0
2	5	3	4	5	10	3	0
3	5	2	4	4	9	2	0
4	5	1	4	3	8	1	0
5	5	0	4	2	7	0	0
6	5	0	3	2	6	-	-1
7	5	0	2	2	5	-	-2
8	5	0	1	2	4	-	-3
9	5	0	0	2	3	-	-4

Table 6.3: Bundle pricing through best response for instance 3.

- Shipper: cost with 5

6.4 Conclusions

In this chapter, we improve the bilevel model by introducing the competition among carriers, it leads to the multi-leader single-follower bilevel model, the problem investigate the truth that the carriers are decentralized and we study how it affect the final solution.

In the experiment results, we show that: 1, introducing conflicting lanes can largely lower the shipper's cost, instance 2 and 3 gives less cost for shipper comparing with instance 1; 2, as seen in all instances, request $R1$ is the request only in carrier $C1$'s bundles, this request will always keep the highest price in the price evolution. This request can be defined as the most attractive request. If we can identify all the attractive requests in the large instances, it will save a lot of computational time.

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Conclusions and Perspectives

In this thesis, we have defined models and decision-making algorithms to design simultaneously several sustainable logistics and transportation chains between origins and destinations for a given logistics and transportation network. These problems typically involve Bundle Construction Problem (BCP), Winner Determination Problem (WDP), Bid Generation Problem (BGP), and Bundle Pricing Problem (BPP) under the transportation procurement system. These problems are addressed from two perspectives. In the first case, centralization is considered among carriers, the best set of chains or the system optimum need to be found. In the second case, the system is shared by all self-interested actors and is decentralized. Carriers put their offers for given origins and destinations flows, then, a combinatorial auction mechanism is applied to compute the final allocation. The main contributions are as follows,

In Chapter 2, the basic concepts and information for decentralized logistics and transportation system are given. We present a classification of the transportation procurement auctions especially the CAs. The bidding language is discussed to be used in CAs. In CAs for transportation procurement, the BCP and BPP are reviewed under BGP and the basic formulation were given for BGP and WDP. Next, we review bilevel problems and showed how/why it can be used to improve the solution in CAs.

In Chapter 3, a detailed survey about WDP is given to summarize the general and variants of the formulations for WDP. The complexity of the problem is analyzed. The most popular benchmarks are classified and the performance of the algorithms are compared.

In Chapter 4, we study the BCP in CAs for full truckload transportation procurement. We define informed carrier and a simplified requests network, and propose a mixed integer linear programming formulation. A bounded exact bi-

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directional dynamic programming is used to solve the problem. The results define a non-dominated solution set instead of only the optimal solution.

In Chapter 5, we merge the BGP and WDP as the single-leader single-follower pricing-allocation bilevel model to express the interactions between shippers and carriers. We define two general bilevel formulations and prove the model with carriers/shipper at the upper/lower level is useful. We also propose a formulation by introducing the risk cost at the lower level to represent the service quality of the carriers. The problem is solved by using the linearization procedure at both upper and lower level. The individual lane pricing and bundle pricing strategies are evaluated and compared in the experimental tests. We show that the risk cost can generate savings for shipper but it increases the computation time of the algorithm. We also show that the informed carriers has the obvious advantage to cover bundles both in qualities and in quantities.

In Chapter 6, we propose a multi-leader single-follower bilevel formulation to represent the carrier interactions. It corresponds to the decentralized setting where the carriers are competitively putting their offers. The problem is solved by best response dynamics under multiple round CAs.

The topics covered in this thesis provide some management insights for decentralized logistics and transportation systems. However, there is still room for new research developments. In the following, we list several research directions that we believe are of interest.

The first two perspectives considers the methodology,

- In this thesis, the BCP problem is solved through an exact bi-directional dynamic programming. The solution can not guaranteed to be optimal unless the forward and the backward extension are mapped on all searching area, i.e. the *Halfway* point is extended to T . This procedure is very time consuming. Therefore developing heuristics to solve the problem efficiently and to simultaneously determine the non-dominated solution set could be useful.
- Second, the bilevel formulations developed and the algorithms used for centralized and decentralized pricing-allocation problem need to be further improved to solve large and realistic instances. Indeed, solving Mixed-Integer Bilevel Linear Program (MIBLP) is much more challenging than single level

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Mixed-Integer Linear Program (MILP): first of all, MIBLPs are \sum_2^P -hard. Furthermore, it is known that allowing continuous variables in the leader and integer variables in the follower, may lead to bilevel problems whose optimal solutions are unattainable. Finally, in contrast to single-level MILPs, unboundedness of a relaxation of the problem does not allow to draw conclusions on the optimal solution of MIBLP. More precisely, MIBLPs with unbounded relaxation value can be unbounded, infeasible, or admit an optimal solution. DeNegre & Ralphs (2009); Fischetti *et al.* (2018) demonstrated how to turn a standard branch-and-bound MILP solver into an exact and finitely-convergent MIBLP, and possible linear inequalities and cuts could be introduced to solve the problems more efficiently. However, the solution methods in Fischetti *et al.* (2018) rely on a strong assumption where the leader variables do not appear in the follower problem, which is not our case.

The second perspectives are associated with the application,

- In this thesis, the BCP problem is formulated for full truckload freight transportation. Few research is found for less than truckload freight transportation. In less than truckload freight transportation, a lane is defined as an origin-destination pair together with a volume of shipment needed to be transported from the origin to the destination, and the bidding price $v_i(S)$ is defined for one unit volume S by bidder i . The BCP formulation could be extended when capacity is integrated in the routing construction problem, but it will increase the complexity of the problem both in modeling and computation.
- Another perspective of the BCP is to investigate the dynamic version of the routing construction problem under the same setting. Indeed, in the more realistic applications, new lane requests are arriving randomly or lane exchange (Özener *et al.*, 2011) may be allowed during the planning horizon, then a new solution has to be recomputed.
- Furthermore, risk costs in shipper's objective are either bundle oriented or carrier oriented. More precisely, risk is fixed when the number of lane in a bundle is fixed or a carrier is given. In a more realistic way, the shipper

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may develop numerical rating for each carrier to define his service quality level.

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Résumé Etendu

De nos jours, le transport de marchandises ou le camionnage est une composante vitale de l'économie et de la chaîne d'approvisionnement. En Europe, le transport de marchandises contribue à environ 5 % du PIB total, et parmi tous les modes de transport, le transport routier de marchandises partage près de 80 % des activités de transport intérieur en raison de la flexibilité et de la capacité à fournir des services porte-à-porte efficaces et rapides dans la plupart des pays, voir la Figure.1.1. Aux États-Unis, le camionnage par camion a partagé près de 70 % du marché du transport de marchandises (voir Figure.1.2), et le total des revenus d'exploitation (voir Figure.1.3) et le revenu total (voir Figure. 1.4) continue d'augmenter en raison de la mondialisation du commerce et de la croissance économique. Comme en France, la contribution au PIB des transports en France est de 14 % soit 321 milliards d'euros, et 5,4 % PIB provient du transport de marchandises (Insee, 2018 *).

Cependant, les transporteurs du marché du transport de fret sont confrontés à plusieurs défis pour conserver et élargir leur part de marché et ainsi améliorer leurs revenus. L'un des défis vient de la concurrence de plus en plus intense à trois niveaux: entre les pays et les régions, entre les différents modes de transport et entre les nombreux transporteurs et prestataires de services logistiques. Dans cet environnement concurrentiel fort, les expéditeurs et les transporteurs sont sous pression pour réduire leurs coûts et opérer plus efficacement, et en réponse à ces défis, dans cette thèse, nous étudions les systèmes de logistique et de transport centralisés et décentralisés.

Dans les systèmes de logistique et de transport centralisés, plusieurs expéditeurs ou transporteurs collaborent étroitement pour optimiser les opérations de transport en partageant les capacités de transport et les demandes de livraison.

*<https://www.unionroutiere.fr/publication/consultez-faits-chiffres-2018/>

Résumé Etendu

Cependant, les marchés du monde réel sont essentiellement distribués - décentralisés. Les expéditeurs et les transporteurs intéressés ont des préférences privées, ils se comportent de manière stratégique pour atteindre une meilleure efficacité et augmenter leurs propres profits. Ce système est appelé les systèmes de logistique et de transport décentralisés. Dans ce système, tous les acteurs indépendants doivent interagir de manière intéressée.

Cette thèse se poursuit dans le cadre d'un projet ANR, «pi-co-modalité». Les partenaires sont le Centre de Gestion Scientifique de Mines ParisTech, DHL Service Central, l'INRIA Lille-Nord Europe et le CNRS LAAS. Le projet pi-co-modalité est consacré à la conception de chaînes co-modales entre les origines et les destinations en fonction d'objectifs environnementaux et économiques. Le terme " co-modal " est un terme utilisé pour la première fois par l'UE en 2006 et fait référence à l'utilisation intelligente de deux ou plusieurs modes de transport seuls et en combinaison pour tirer le meilleur parti de chacun d'eux afin que le trajet global soit le plus durable. que cela peut être. Cette optimisation de l'utilisation des ressources présente des avantages économiques, environnementaux et sociétaux. Le projet est basé sur le concept d'Internet physique (raccourci par PI) (Montreuil, 2011) qui rompt avec les approches établies précédemment. La métaphore de l'internet numérique est utilisée pour illustrer les concepts clés. En tant que paquets numériques sur des réseaux informatiques interconnectés, le PI vise à développer un système logistique global basé sur l'interconnexion de réseaux de services logistiques pour transférer des marchandises entre les origines et les destinations.

Dans le projet ANR, le problème de la conception de chaînes durables multimodales est abordé sous deux angles. Dans le premier cas, on considère un système centralisé ou «système optimal» où un expéditeur est en charge de définir le «meilleur» ensemble de chaînes. Dans le second cas, le système est partagé entre les acteurs et décentralisé. L'expéditeur précisera le cadre général (les plateformes multimodales potentielles à utiliser) et les origines et destinations des flux. Ensuite, les entreprises de transport présenteront leurs offres, qui seront considérées selon un mécanisme d'enchères combinatoires. Cela se traduira par une activité logistique partagée qui optimise l'utilisation des ressources.

Le sujet de ma thèse est d'aborder la situation décentralisée et d'étendre le concept PI de manière plus réaliste. Afin d'atteindre des performances de haut

niveau dans des environnements décentralisés, un cadre général constitué d'un centre d'enchères potentiel joue le rôle d'intermédiaire de marché. Entre l'origine (c'est-à-dire les expéditeurs) et la destination (c'est-à-dire les clients), les hubs jouent le rôle de centre de transit des marchandises pour augmenter l'efficacité de l'allocation du système. Tous ces acteurs avec leurs propres intérêts, leurs atouts, leurs sous-réseaux et leur indépendance sont considérés.

L'objectif global de cette thèse est de s'appuyer sur une approche de «conception de mécanisme», elle permet aux agents allouant des faisceaux de voies à un ensemble de transporteurs de définir la solution entre les acteurs, et d'améliorer les performances du mécanisme porté par tous les acteurs. En d'autres termes, l'objectif principal est de concevoir un mécanisme d'enchères et une plate-forme, pour faciliter l'adéquation entre l'offre et la demande entre les expéditeurs et les clients; pour obtenir des informations utiles pour la mise en œuvre pratique de ces mécanismes, qui **conduiront à l'allocation des ressources de transport mondiales la plus efficace**. La solution devrait encourager les expéditeurs et les transporteurs à utiliser le mécanisme d'enchères plutôt qu'à se comporter individuellement, de sorte que tous les agents intéressés aient un meilleur intérêt à appliquer la solution conçue par la plateforme plutôt que d'appliquer la solution de base d'intérêt personnel.

Dans l'étude de cette thèse, plusieurs parties se posent,

- Premièrement, des approches d'enchères sont utilisées pour faciliter l'appariement entre les demandes de transport et les fournitures, ce qui fait référence aux `textbf` enchères d'approvisionnement en transport;
- deuxièmement, **méthodes de construction de routage** sera utilisé pour construire un faisceau de voies;
- et enfin un **problème de génération d'enchères** et **problème de détermination du gagnant** sont résolus pour réaliser l'appariement de l'offre et de la demande.

D'un point de vue méthodologique, nous nous sommes appuyés sur l'IP pour modéliser le réseau maillé et sur une «approche de conception de mécanismes» pour définir des faisceaux d'itinéraires pour les transporteurs, afin d'augmenter l'objectif du système; puis nous avons utilisé un modèle d'allocation des prix

à deux niveaux pour déterminer l'attribution des voies aux transporteurs, afin d'explorer pleinement les comportements d'interaction entre l'expéditeur et les transporteurs.

Dans cette thèse, nous avons pour objectif de développer des modèles et des algorithmes de prise de décision pour concevoir simultanément plusieurs chaînes de logistique et de transport durables entre les origines et les destinations compte tenu d'un réseau logistique et de transport. Ces problèmes impliquent généralement un problème de construction groupée (BCP), un problème de détermination du gagnant (WDP), un problème de génération d'enchères (BGP) et un problème de tarification groupée (BPP) dans le cadre du système d'approvisionnement en transport. Ces problèmes sont abordés sous deux angles. Dans le premier cas, la centralisation est envisagée entre les transporteurs, il faut trouver le meilleur ensemble de chaînes ou l'optimum du système. Dans le second cas, le système est partagé par tous les acteurs intéressés et il est décentralisé. Les transporteurs déposent leurs offres pour des flux d'origines et de destinations donnés, puis un mécanisme d'enchères combinatoires est utilisé pour calculer l'allocation finale. Les principales contributions sont les suivantes,

Au chapitre 2, les concepts et informations de base pour la logistique décentralisée et le système de transport ont été donnés. Nous avons présenté une classification des enchères d'achat de transport en particulier les enchères combinatoires (CAs), le langage des enchères a été discuté pour être utilisé dans les CAs. Dans les CAs pour les achats de transport, le BCP et le BPP ont été examinés sous BGP et la formulation basique a été donnée pour BGP et WDP. Dans le dernier, nous avons examiné les problèmes à deux niveaux et montré comment/pourquoi il peut être utilisé pour améliorer la solution dans les CAs.

Dans le chapitre 3, une enquête détaillée sur WDP a été donnée pour résumer le général et les variantes des formulations pour WDP. La complexité du problème est analysée, il a suivi les algorithmes exacts et approximatifs utilisés pour résoudre WDP avec précision et efficacité. Les benchmarks les plus utilisés ont été classés et les performances des algorithmes ont été comparées.

Au chapitre 4, nous avons étudié le BCP dans les CAs pour l'approvisionnement en transport par camion complet. Nous avons défini un transporteur informé et un réseau de requêtes simplifié, et proposé une formulation de programmation

linéaire en nombres entiers mixtes. Une programmation dynamique bidirectionnelle exacte bornée a été utilisée pour résoudre le problème, elle a fourni un ensemble de solutions non dominé au lieu de seulement la solution optimale.

Au chapitre 5, nous avons fusionné le BGP et le WDP en tant que modèle à deux niveaux d'allocation de prix centralisé pour exprimer l'interaction entre l'expéditeur et les transporteurs. Nous avons proposé deux formulations générales à deux niveaux et prouvé que les transporteurs/expéditeurs au niveau supérieur/inférieur sont utiles. Nous avons également proposé une formulation en introduisant le coût du risque au niveau inférieur pour représenter la qualité de service des transporteurs. Le problème a été résolu en utilisant la procédure de linéarisation aux niveaux supérieur et inférieur. Les stratégies de tarification des voies individuelles et de tarification groupée ont été évaluées et comparées dans les tests expérimentaux. Nous avons montré que le coût du risque peut générer des économies pour l'expéditeur mais il a augmenté l'effort de recherche de l'algorithme. Nous avons également constaté que les transporteurs avertis ont l'avantage évident de couvrir les paquets tant en qualité qu'en quantité.

Dans le chapitre 6, nous avons proposé une formulation bi-niveau multi-leader mono-suiveur pour représenter l'interaction des transporteurs, cela correspond au cadre décentralisé où les transporteurs mettent leurs offres de manière compétitive. Le problème a été résolu par la meilleure dynamique de réponse sous plusieurs CAs rondes.

Models and methods for decentralized decision in logistics networks

Abstract

In this thesis, we aim to develop models and decision making algorithms to design simultaneously several sustainable logistics and transportation chains between origins and destinations given a logistics and transportation network. First, we investigate the state of the art of decentralized logistics and transportation systems, and survey the Winner Determination Problem. Then, we study the Bundle Construction Problem to construct transportation routes, which is solved by an exact bi-directional dynamic programming. Next, we merge the Bid Generation Problem and Winner Determination Problem through bilevel concept, the centralized and decentralized bilevel problems are then solved by Linearization procedure and Best Response procedure, respectively.

Keywords: Bilevel Optimization, Integer Programming, Decentralized Transportation System, Bundle Construction Problem, Winner Determination Problem, Bid Generation Problem.

Modèles et méthodes de décision décentralisée dans les réseaux logistiques

Résumé

Dans cette thèse, nous avons pour objectif de développer des modèles et des algorithmes de prise de décision pour concevoir simultanément plusieurs chaînes de logistique et de transport durables entre origines et destinations compte tenu d'un réseau de logistique et de transport. Tout d'abord, nous étudions l'état de l'art des systèmes de logistique et de transport décentralisés et étudions le problème de la détermination des gagnants. Ensuite, nous étudions le problème de construction de paquets pour construire des itinéraires de transport, qui est résolu par une programmation dynamique bidirectionnelle exacte. Ensuite, nous fusionnons le problème de génération d'enchères et le problème de détermination du gagnant via un concept à deux niveaux, les problèmes à deux niveaux centralisés et décentralisés sont ensuite résolus par la procédure de linéarisation et la procédure de meilleure réponse, respectivement.

Mots clés : Optimisation à deux niveaux, programmation d'entiers, système de transport décentralisé, problème de construction de lots, problème de détermination du gagnant, problème de génération d'enchères.
