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The Bid Generation Problem in Combinatorial Auctions for Transportation Service Procurement

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The Bid Generation Problem in Combinatorial Auctions for Transportation Service Procurement

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Scuola di Dottorato in Ingegneria dei Sistemi, Informatica, Matematica, Ricerca Operativa

Il Problema di Generazione delle Offerte nelle Aste Combinatorie per Procurare dei Servizi di Trasporto

Tesi sottomessa per il conseguimento del
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In the memory of my beloved mother

Contents

Summary in Italian

Nell'ambito del presente lavoro di tesi *è* stato affrontato un problema di rilevante interesse applicativo relativo alla valutazione e generazione di offerte (Bid Generation Problem) nell'ambito di aste combinatorie per sistemi di trasporto di tipo full-truckload (a pieno carico).

L'organizzatore (auctioneer) di un'asta combinatoria, vuole acquistare tramite asta dei servizi (contratti) di trasporto, cio*è* rotte (lane) su cui trasportare dei carichi (load). I vari trasportatori (carrier) devono quindi fare delle offerte (bid) sulle rotte di trasporto che vogliono vendere all'asta, non in maniera individuale (come nelle aste singole), ma raggruppate in pacchetti (bundle) di rotte.

Il Bid Generation Problem (BGP) in un'asta combinatoria *è* il problema affrontato dal carrier per poter costruire tali offerte (bundle di rotte) da sottomettere all'asta sotto forma di bid (cio*è* l'insieme di load con il relativo prezzo proposto).

Le aste combinatorie sono di solito scelte per procurare i servizi di trasporto per via delle sinergie che usualmente esistono tra le varie rotte messe all'asta e quelle componenti la rete di trasporto attuale di un carrier. La necessit*à* di valutare un numero esponenziale di bundle (pari al numero di tutti i sottoinsiemi che si possano formare con le rotte messe all'asta) conferisce al problema decisionale una natura NP-completa, come evidenziato ad esempio in [33]. La scarsit*à* dei riferimenti bibliografici, se pur motivata dall'oggettiva difficolt*à* di soluzione sopra descritta, non ha giustificazioni per*ò* dal punto di vista applicativo.

In tale ambito si colloca la presente tesi di Dottorato avente come obiettivo lo sviluppo di un *advisor* che assista i carrier nelle loro decisioni di bidding, integrandosi nella pianificazione dinamica delle operazioni di trasporto. In particolare, nel lavoro di tesi *è* stato proposto un modello di ottimizzazione misto intero per il BGP in grado di determinare non solo il bundle di load sottomesso all'asta e il relativo prezzo, ma anche il relativo routing della flotta del carrier, effetuato nell'orizzonte temporale per servire sia il bundle di rotte sottomesso che la rete di trasporto attuale.

I principali contributi innovativi del modello proposto derivano da:

1) l'inclusione nel modello di un vincolo di tipo probabilistico (chance constraint), che mira a guidare la scelta del bundle con maggiore chance di vincita alla fine dell'asta, cio*è* la cui probabilit*à* di superare il clearing price (rappresentato tramite una variabile aleatoria) sia superiore ad un certo livello di probabilit*à*. Rispetto al modello di Savelsbergh et al. ([54]), si considera la probabilit*à* che il bundle sia vincente nei vincoli invece che nella funzione obiettivo, e la distribuzione normale del clearing price (pi*ù* realistica) invece di quella uniforme. Inoltre, in [54], si trattava di pi*ù* aste singole indipendenti, svolte in parallelo, qui invece abbiamo un'asta combinatoria a busta chiusa, primo prezzo, single-round.

2) il considerare il prezzo del bundle come variabile di decisione, come solo in [54] accadeva , negli altri articoli si considera o qualche formula di calcolo ([42], [52], [53]) oppure noti, fissati uguali alla somma dei prezzi richiesti dall'auctioneer (ask price) per le singole rotte componenti il bundle ([6],[24]).

3) l'inclusione dell'aspetto temporale del problema reale (finora solo Chang aveva considerato in [6] la rete estesa spazio-tempo per il BGP).

4) il determinare anche il routing dei camion relativo a tutto l'orizzonte temporale ([24] era il primo articolo che, nel modello proposto per il BGP, includeva anche il VRP, ma senza per*ò* considerare la variabile tempo).

5) l'inclusione delle finestre temporali (time-windows) relative alla

consegna di ogni carico messo all'asta e dei carichi della rete attuale di trasporto (precedentemente contrattati) dal carrier.

6) lo studio e la quantificazione delle sinergie tra le rotte messe all'asta e quelle dell'attuale rete di trasporto del carrier (in due modi, e diversamente di come fatto in [2], [6], [54], [58]) e l'inclusione di tali sinergie nella distribuzione della variabile aleatoria considerata (il clearing price del bundle).

Per i motivi sopra descritti, il modello proposto risulta più completo e più complesso rispetto a tutti i modelli finora esistenti per il BGP nelle aste combinatorie nei trasporti a pieno carico.

Il presente lavoro è organizzato in 5 capitoli, esclusa l'introduzione e le conclusioni. Nel seguito viene riportata una breve descrizione del contenuto di ogni capitolo. La tesi inizia con una introduzione al presente lavoro.

Nel capitolo 1 vengono introdotte le aste combinatorie, partendo dalla loro definizione e descrizione(fasi dell'asta), alla loro classificazione rispetto vari criteri, agli svantaggi e vantaggi rispetto alle aste normali, evidenziati nella letteratura esistente.

Nel capitolo 2 sono descritte, partendo dalla letteratura, le aste combinatorie utilizzate per procurare servizi (contratti) di trasporto nel caso full-truckload e forniti esempi di aste. Inoltre, vengono descritti i problemi presenti in un asta combinatoria: il problema di generazione e valutazione delle offerte (*Bid Generation Problem*, BGP) ed il problema di determinazione del vincitore (*Winner Determination Problem*, WDP), ed evidenziata la loro difficoltà di soluzione (problemi NP-hard).

Il capitolo 3 è dedicato al BGP, oggetto di studio di questa tesi. Dopo aver presentato lo stato dell'arte relativo al BGP, viene riportato un modello originale proposto per il BGP, evidenziando le novità di tale modello e le complicazioni rispetto ai modelli esistenti nella letteratura. Vengono illustrate le difficoltà di risoluzione di tale modello (dovute al numero esponenziale dei bundle, quindi dei vincoli e delle variabili, ecc...).

Con l'obiettivo di superare a priori il problema della dimensione, quindi per diminuire la cardinalità dell'insieme dei bundle possibili, sono state sviluppate delle procedure di preprocessamento dell'insieme delle rotte messe all'asta, tenendo conto sia dalla posizione dei camion che dalle finestre temporali di consegna dei carichi. Inoltre, sono state studiate e quantificate le sinergie tra le rotte messe all'asta e quelle dell'attuale rete di trasporto del carrier (in due modi, e diversamente di come fatto in [2], [6], [54], [58]) ed incluse nella distribuzione della variabile aleatoria considerata (il clearing price del bundle). Vengono presentati i chance constraints ed effettuata una discussione relativamente alla distribuzione ed all'indipendenza delle variabili aleatorie rappresentando i clearing price dei load componenti il bundle.

Diverse versioni di tale modello sono state prodotte a partire dalla formulazione iniziale, includendo la sinergia nella funzione obiettivo e/o nei vincoli, considerando finestre temporali di prelievo dei carichi, considerando vincoli di copertura delle rotte (come in [51], [53]), riformulando il modello tale che la rete spazio-tempo sia esplicita.

Nel capitolo 4 viene proposto un approccio risolutivo di tipo euristico in quanto l'elevata dimensione (esponenziale) del problema ha permesso la soluzione esatta soltanto fino ad una certa cardinalità del insieme di rotte messe all'asta. Per dimensioni superiori sono state costruite delle euristiche che permettono una risoluzione sequenziale del problema.

Una prima categoria di euristiche, partendo dal bundle di load di cardinalità massima, cioè uguale all'insieme dei load messi all'asta, valuta il profitto decrementale (beneficio marginale) di ogni bundle ottenuto togliendo un load del bundle corrente alla volta, sceglie il load in corrispondenza di cui si è ricavato il migliore profitto decrementale, aggiorna il bundle corrente (eliminandone il load selezionato) e così via. Il procedimento è ripetuto fino a quando il bundle corrente non risulta vuoto. Una variante di questa euristica è ottenuta partendo dal bundle di cardinalità minima (vuoto, per esempio) e valutando il profitto incrementale (all'aggiunta di un load al bundle corrente). La complessità sarà soltanto dell'ordine di n^2 (con n la cardinalità dell'insieme di load messe all'asta).

Una seconda categoria di euristiche considera come insieme dei bundle iniziali un certo insieme di bundle scelti secondo vari criteri (random, quelli con maggiore sinergia e/o compressa in qualche intervallo, di cardinalità compressa in qualche intervallo, etc...). Risolve il problema per ogni bundle di tale insieme e seleziona tra essi il bundle di massimo valore della funzione obiettivo.

Il capitolo 5 è relativo alla fase sperimentale condotta al fine della valutazione della correttezza (validazione) del modello e delle prestazioni dei metodi risolutivi proposti in termini di efficienza ed efficacia. Come ambienti di sviluppo (implementazione e soluzione) del modello sono stati usati GAMS, Microsoft Visual C++, ILOG CPLEX ed ILOG CONCERT. Dal momento che per le aste combinatorie non sono in generale disponibili pubblicamente i dati reali (come spesso viene segnalato in letteratura, per esempio in [2]), si è costruito anche un generatore di problemi test, implementato in C. A causa del numero esponenziale di vincoli e variabili (relativi ai bundle di load messi all'asta), il modello proposto è stato risolto in maniera esatta soltanto fino ad una certa dimensione (20 rotte messe all'asta). Per dimensioni superiori sono state utilizzate le euristiche proposte per una risoluzione sequenziale del problema. Vengono effettuati dei confronti tra le varie euristiche proposte implementate, fornendo il gap con la soluzione ottima ed i relativi tempi computazionali.

I risultati preliminari ottenuti sono molto incoraggianti e mostrano l'efficacia e l'efficienza delle strategie risolutive sviluppate e l'utilità del modello proposto in termini di strumento in grado di supportare i carrier nelle decisioni integrate di routing della flotta e di bidding profittevoli.

La tesi chiude con la parte relativa alle conclusioni del lavoro ed alla ricerca futura.

Il lavoro di tesi rappresenta un valido studio ed una scrupolosa analisi delle problematiche riguardanti il BGP in un asta combinatoria nei trasporti di tipo full truckload. Il maggior contributo scientifico *è* stato quello di aver presentato e definito un modello matematico per la valutazione e la generazione di offerte (integrando anche il routing della flotta dei carrier) e delle procedure euristiche in grado di risolverlo su istanze pi*ù* complesse.

Introduction

In this thesis has been studied a relevant applicative interest problem (the Bid Generation Problem) related to the generation and evaluation of the bids in combinatorial auctions for the procurement of full truckload transportation services.

0.1 Motivation

In a combinatorial auction the auctioneer wants to procure transportation services, that is lanes on which there are carried loads. The various carriers had to make some bids on the transportation lanes that want to sell during the auction, not individually (like in normal auction), but grouped in packages (bundles) of lanes.

The Bid Generation Problem (BGP) in a combinatorial auction is the problem faced by the carrier in order to construct such bundles of loads to submit in the auction as bids (that is the set of proposed loads with their corresponding price).

The combinatorial auctions are usually chosen in order to provide transportation services because of the synergies between the auctioned lanes and those of the current transportation network of the carriers. Examples of companies using combinatorial auctions to procure logistics services are: Sears Logistics Services, The Home Depot; Walmart Stores, Compaq Computer Co., Staples Inc., The Limited Inc., Limited Logistics Services, Kmart Corporation (aided by Logistics.com)([9]).

The necessity to evaluate an exponential number of bundles (equal to the number of all possible subsets that can be made with the auctioned loads) brings to the decisional problem a NP-complete nature, as highlighted for example in [33]. The lack of bibliographic references, even if justified by the objective difficulty of solution of the BGP previously described, does not have motivation from the applicative point of view.

0.2 Goals

The present Ph.D. thesis fits in this context, having as goal the development of an *advisor* that assists carriers in their bidding decisions, integrated in the dynamic planning of the transportation operations. In particular, in this thesis a mixed integer optimization model has been proposed for the BGP, being able to determine not only the bundle of loads submitted in the auction and its corresponding price, but even the corresponding routing of the fleet of the carrier, made in the temporal horizon, in order to serve both the submitted bundle of loads and the carrier's current transportation network.

Therefore, the main aim of this thesis is the definition, the design, the implementation and the test of innovative models and methods computationally efficient for the BGP in combinatorial auctions for the procurement of full truckload transportation services.

0.3 Contribution

The main innovative contributions of the proposed model and its variants derive from:

- the inclusion in the model of a probabilistic-type constraint (chance constraint), which looks up to guide the selection of the bundle with the highest winning chance at the end of the auction, that is whose probability of exceeding the clearing price (represented by means of a random variable) is greater than a certain probability level. Unlike the model of Savelsbergh et al. ([54]), we consider the winning probability of the bundle in the constraints instead in the objective function and the normal distribution of the clearing price (more realistic) instead of the uniform one. Moreover, the paper [54] is concerning several single independent auctions simultaneously run, here instead we consider a sealed-bid, first-price, single-round combinatorial auction.

- considering the price of the bundle as a decision variable, like only in [54] occured, while in other papers the bundle's price is computed by using some formula ([42], [52], [53]) or is considered known, fixed equal to the sum of the auctioneer's ask prices for the single loads which form the bundle ([6],[24]).

- the inclusion of the temporal aspect of the real problem (until now only Chang had considered in [6] the space-time extended network for the BGP).

- the determination of the routing of the truck relative to all the temporal horizon (only [24] included the VRP in the proposed model for the BGP, but without consider the time variable).

- the inclusion of the time windows relative to the delivery of every auctioned load and of the loads of the carrier's existing transportation network (previously auctioned).

- the study and the computation of the synergies between the auctioned loads and those of the carrier's existing transportation network (in two ways, and differently as done in [2], [6], [54], [58]) and the inclusion of these synergies in the distribution of the random variable representing the clearing price of the bundle.

Because of all the previously described reasons, the proposed model results more complete and more complex respect to all the already existing models for the BGP in combinatorial auctions for the procurement of full truckload transportation services.

The huge, exponential dimension of the problem have permitted the exact solution only up to certain cardinality of the set of the auctioned loads. For higher dimensions some heuristic procedures that permit a sequential solving of the BGP have been constructed. The behaviour of the proposed solution approaches was evaluated on a wide range of test problems generated by ourselves.

0.4 Organization of the thesis

The thesis is organized in five chapters, introduction and conclusions excluded.

In the following a brief description of the content of each chapter is reported. The thesis begins with an introduction of the present work.

In chapter 1 the combinatorial auctions are introduced, starting from their definition and description (the auction's stages), to their classification respect to various criteria, to benefits and drawbacks respect to normal, simple auctions, highlighted by the existing scientific literature.

In chapter 2, starting from the literature, the combinatorial auctions used to procure transportation services (contracts) in the full-truckload case are described and examples provided, as well. Moreover, we propose a detailed description of the problems of a combinatorial auction: the *bid generation and evaluation problem* (BGP) and the {emphwinner determination problem (WDP) and highlight their difficulty of solution (NP-hard problems).

Chapter 3 is devoted to the BGP, the main subject of this thesis. After presenting the BGP's state of art, we propose an original model for the BGP, by highlighting the new aspects of such a model and the additional difficulties respect to the existing models in the literature. The difficulties of solution of this model are illustrated (due to the exponential number of bundles, hence of variables and constraints, etc...). In order to partially solve a priori the dimensional problem, and so to decrease the cardinality of the set of all possible bundles, there have been developed preprocessment procedures of the set of the auctioned loads, taking into account both of the trucks' position and the loads' delivery time windows. Moreover, the synergies between auctioned loads and those of the carrier's existing transportation network have been studied and quantified (in two ways, and differently as done in [2], [6], [54], [58]) and included in the distribution of the random variable representing the clearing price of the bundle. We present the chance constraints and discuss the distribution and the independence of the random variable representing the clearing prices of the loads components the bundle. Different variants of this model have been produced beginning with the initial formulation, including the synergy in the objective function and/or in the constraints, considering loads' pick-up time windows, considering lane covering constraints (like in [51], [53]), reformulating the model such that the time-space extended network be explicite.

In chapter 4 an heuristic-type solution approach is proposed because the huge (exponential) dimension of the problem allowed the exact solution only up to certain cardinality of the set of the auctioned loads. For higher dimensions some heuristic procedures that permit a sequential solving of BGP have been constructed.

A first type of heuristics, starting from the maximal cardinality bundle of loads (that is, equal to the set of the auctioned loads L), evaluate the decremental profit (marginal benefit) for each bundle obtained by dropping out one load at a time from the current bundle, and choose the load for whom it has been yield the best decremental profit. Then update the current bundle (eliminating the previously selected load) and so on. The procedure is repeted until the current bundle becomes empty.

A version of this heuristic can be obtained by considering as the initial bundle that one with minimal cardinality (for example, the empty set) and evaluating the incremental profit get by adding a load to the current bundle. The complexity of this first type of heuristic algorithms will be only of $\mathcal{O}(n^2)$ (where n is the cardinality of the set of the auctioned loads).

A second type of heuristics considers as the initial set of bundles a certain set of bundles selected with respect to various criteria (random selection, bundles chosen with higher synergy and/or in some interval, bundles with cardinality in some interval, etc...). Then the problem for every bundle of this set (constructed as above) is solved and, moreover, we select from these the bundle with maximum value of the objective function.

Chapter 5 is related to the extensive computational phase carried out in order to validate the model and evaluate, in terms of efficiency and efficacy, the performances of the proposed solution methods. GAMS, Microsoft Visual C++, ILOG CPLEX ed ILOG CONCERT have been used as development (implementation and solving) environment of the model. Since for the combinatorial auctions the real data are not usually publicly available (as often pointed out in the scientific literature, for example in [2]), we constructed and implemented in C a test problems' generator. Because of the exponential number of variables and constraints (corresponding to the bundles of auctioned loads), the proposed model has been solved exactly only up to a certain dimension (20 auctioned loads). For higher dimensions the proposed heuristic procedures that permit a sequential solving of the BGP have been used. Extensive computational tests are carried out on a meaningful number of test problems, with the goal of assessing the behaviour of the proposed approaches. Thus, the various proposed heuristics have been compared, providing the gap with the best (optimal) solution and the corresponding computational times. The preliminar results are very encouraging and show the efficacy and the efficiency of the developed solving strategies and the usefulness of the proposed model in terms of tool to support the carriers in their integrated fleet routing and profitable bidding decisions.

Conclusions (and future work projects) are given at the end of the thesis.

This thesis represents a rigorous study and an accurate analysis of the problems related to the BGP in a combinatorial auction for full truckload transportation. The main scientific contribution is the introduction and the definition both of a mathematical model for the bid generation and evalutation (integrating also the routing of the carriers' fleet) and of the heuristic procedures able to solve the BGP on more complex instances.

Chapter 1

Combinatorial Auctions

1.1 Introduction

Auctions have been used since ancient times. The first auctions took place as early as 500 B.C, as is generally accepted. Perhaps one of the most spectacular auctions in history occurred in 193 A.D. when the throne to the Roman Empire was auctioned to the highest bidder by the Praetorian Guard, after having killed the emperor Pertinax ([16]).

Today auctions are known to be an efficient way for selling and procuring items of different nature. For example, auctions are used when trading oil, gas, timber, mineral rights, radio frequency rights, services contracts, collectibles of all kinds and so on. There are numerous on-line auction websites, and auctions have even made their way into the on-line gaming scene.

McAfee and McMillan ([29]) define auctions as market institutions with an explicit set of rules determining resource allocation and prices, based on bids from the market participants. An auction could be viewed as a method of commerce where the auctioneer elicits price information from bidders through the submission of bids. A winner is selected based on an allocation rule which takes into account only the submitted bids, and the winner pays some amount specified by a payment rule. In traditional (standard) auctions, the allocation rule is to award the item to the highest bidder, but this does not have to be the case more generally.

Many auctions concern the selling or procuring of a single item (single-item auctions). Examples of widely applied single-item auction protocols, both in practice and in the scientific literature, known as the main four types of "'classical"' auctions ([57],[19]), are:

- **Open ascending price auction (English auction)** : the auctioneer starts with a *reservation price*, the lowest acceptable price, and the price is raised with every new bid, the bidders dropping out of the auction when they are not willing to bid above the current price. The winner is the last remaining bidder and he pays the price of his bid. Since the auction is open the bids are known to bidders during the auction.
  In the English auction, the auctioneer has the right to keep secret the reservation price. Because of the high competition level between bidders and of the unskilled bidders that raise the price, in this kind of auction it is common the "winner course", that is paying an item more than its real value.

- **Open descending price auction (Dutch auction)**: even if the English auction is the most common (used) kind of auction, the Dutch auction is the first one known in the history; the Babilonians used it for selling young women to rich people.
  In this type of open auction, the bid starts from a extreme price and decreases until a buyer gains the item and pays the last lowest price.

- **First-price sealed-bid auction**: the most important property of this auction is that the bids are submitted in a "sealed envelope", thus are hidden to other bidders. Usually, in this kind of auction every bidder can submit only one bid, hence the choice of the bid results very important.

This kind of auction has two stages: a bid stage, where the buyers submit their bids, and a solving (auction) stage, where the winner of the auction is determined. In a forward sealed bid auction, the winner (the highest bidder) pays the amount bid. In a reverse (or procurement) auction, with one buyer and many sellers, the lowest bid presented by the sellers wins and is payed by the buyer. However, the analysis of selling auctions and procurement auctions is similar.

- **Second-price sealed-bid (Vickrey) auction**: as the first-price auction, in the Vickrey auction the bidders submit bids in a "'sealed envelope"', hence bids are unknown to the other bidders. Highest bidder wins and pays the value of the second highest bid. Even if the first-price auction seems provide major benefits to the seller (auctioneer), in pratice this is not true. In the Vickrey auctions the bidders are not afraid to present high prices and this represents a gain for the auctioneer.

All of the above auctions have been thoroughly analyzed, and bidder behavior has been mapped for many settings.

Even if we have considered only the *single-unit* auctions, the types of auction previously reported could be extended to the *multi-unit* case where more units of the same object are auctioned. For a detailed description of the *multi-unit* auctions see, for example, ([19]).

However, there are cases when a seller has many items that he wishes to sell simultaneously and where buyers have synergies on certain combinations of items. One such example is the shipping industry, and another is the spectrum license auctions held world wide.

There are several ways to approach the sale of multiple items. A classification of the *multi-item* auctions distinguish between ([44]):

- **sequential** auctions
- **parallel** auctions

- **combinatorial** auctions.

In the sequential auctions the items could be sold one after the other, there will be as many auctions as many items are being auctioned. Thus, every item or indivisible set of items is auctioned one at a time. The winner determination is done by simply choosing the best bid for each item. Given its simplicity, the sequential auction was widely used during the past and the most of the auctions used today in the world are of this type.

Another option to sell the items is to auction them simultaneously in several parallel auctions, so in a simultaneous auction.

Yet another way to auction multiple items is by allowing bidders to submit bids not on single items but on indivisible bundles of items, which brings us to combinatorial auctions, our central topic.

The sequential and parallel auctions could lead to inefficient resources allocation. The combinatorial auctions mainly appear in order to overcome these problems.

1.2 Combinatorial auctions

The (***Combinatorial Auctions***) have been proposed for the first time in 1982 by S. Rassenti et al. ([38]). They are *multi-item* auctions in which the bidders can define their own combinations of items (called packages or *bundles*) and can submit bids on them instead of on single items or predefined bundles.

The problem of auctioning multiple goods can be difficult; especially when the valuations of combinations of items differ, or when bidders have preferences over *bundles*. This is often the case in transportation exchanges.

Analyzing combinatorial auctions is hard and compared to single-item auctions relatively little has been done. Since combinatorial auctions are being used more and more, there is a need to study them further.

Combinatorial auctions are computationally hard, but a first-price combinatorial auction really worth pursuing compared to the much simpler simultaneous single-item auction. That because the combinatorial auction captures the synergies between items, and thus the first-price combinatorial auction produces higher revenue than simultaneous single-item auctions.

The combinatorial auctions can be classified as:

- *one-sided*, if there are many buyers and one seller or a buyer and many sellers;
- *multi-item*, if items of different types are sold;
- *multi-unit*, if more units of the same item can be sold.

The *multi-item* auctions are frequent in industrial and logistic supplies (stocks) where the suppliers are able to satisfy the buyers' requests on various items ([48]).

The combinatorial auction permits to the bidders to better express their own preferences and provides more economic efficiency and major auction revenue. This is particularly important for the bidders when the items are sostitutable or complementar: in the latter situation we can talk about **synergies**. There are synergies between items when the sum of the values of the single item is smaller than the value of the *set* consisting of them. For example, a pair of shoes is worth more than the sum of the values of a single unpaired right shoe and a single unpaired left shoe.

Beyond the benefits, however, the combinatorial auctions involve many inherently difficult problems, both for the auctioneer and the bidders ([25]). As mentioned by Song and Regan ([53]), we face the *Bid Construction Problem* where bidders have to compute bids over different job combinations, and the *Winner Determination Problem* where jobs have to be allocated among a group of bidders. Moreover, it may be unrealistic to bundle jobs which belong to different shippers and these procedures are not directly applicable in situations where jobs arrive at different points in time.

The task to solve the ***Winner Determination Problem*** *(WDP)*, that is to find the set of winning bids maximixing the auctioneer's revenue, is fully entrusted to the auctioneer: there will be a set of bids on different *bundles* and from this set is necessary to extract that subset with the highest total value and being a feasible solution of the problem.

In this thesis will not be studied the WDP, but we can affirm that this is a very studied problem in the leterature, even if it is a NP-complete problem, and for this reason it is often solved by using heuristic algorithms trying to provide a solution as near as possible to the best optimal solution.

The problem faced by the bidder in order to evaluate and generate bids (***Bid Generation Problem*** (BGP)) will be studied in detail in the next chapters, dedicated to the use of the combinatorial auctions in transportation industry.

This thesis concerns the interdisciplinary field of combinatorial auctions, combining the fields of operations research, computer science and economics.

1.2.1 Types of combinatorial auctions

The combinatorial auctions can be classified, based on their dynamic, as follows ([49],[35]):

- **one-shot** or *single-round* auctions;
- **iterative** or *multi-round* auctions.

The *one-shot* auctions are sealed-bid and have an unique bidding stage during which all the bidders submit their bids. There are individuated the winning bids by solving the corresponding WDP and are computed the prices to be paid. The design parameters for the *one-shot* auctions are the *bidding language*, the *bid evaluation policy* and the *pricing policy*. The bidding language, studied in detail in the next section, specifies the bids' language, the bid evaluation criterion describes the technique to determine the winners, and the pricing policy determines the prices of the winning items.

The iterative auctions can be sealed-bid or open auctions, but they have more bidding stages. In an iterative auction the bids submission and evaluation are done several times and after every iteration the bidders obtain additional information. These auctions can finish after a established time period or after a certain termination rule has been satisfied (for example, when there are not any new bids). In the most of the iterative auctions, the winner determination and the prices computation are done after any iteration, such that to compute the temporary allocations, while in other auctions are done only after the closing of the auction.

The bidding dynamic adopted in this thesis is *one-shot*, commonly used in the logistic auctions. However, the iterative auctions have been used in a great number of industrial applications, since help the bidders to express their own preferences and to receive information on prices and allocations at every round of the auction ([3]).

As illustated in the previous section, the combinatorial auctions are *one-sided* auctions. These correspond to exchange situations where there is:

(1). a (*seller*) and many (*buyers*) (forward auction);

(2). many sellers and one buyer (reverse auction).

In the *Forward Combinatorial Auction* the seller puts in the auction his own items with a starting price for every item; subsequently there will be the competition between the buyers to establish the market price of the various auctioned items. Therefore, the buyers have the main role, while the seller (auctioneer) has to establish the different criteria of the auction. The goal of this kind of auction is to maximize the seller's profit, that is the auction's profit.

A combinatorial auction where the auctioneer has to buy several goods from the buyers is called (*Reverse Combinatorial Auction*). The aim of this type of auction is, for the buyer, to obtain some goods at the minimum possible cost, and for the sellers, is to sell all the auctioned items, obtaining the best possible revenue both in terms of maximum economic profit and minimum time employed by the buyers in order to finish the activities.

There are two common strategies for the reverse auction:

(1). the buyers assert how much they are willing to pay for an item or a *bundle* of items and the sellers answer with a bid;

(2). the buyers identify the items or the *bundles* of items they are interested to buy without any price indication. The interested sellers submit their bids for the various packages.

The subject of this thesis is a *one-shot* reverse combinatorial auction.

1.2.2 Bidding languages

In an auction, the bid is the expression of the bidder's wish to pay a certain sum of money for different aims. The bidders formulate the bids according to their own preferences and to the bidding strategies.
The bidding languages, defined by Nisan ([32]), indicate how (the message format and the interpretation rules) the bidders can formulate their own bids. The more direct way to formulate a bid is to allow to every bidder to assign a price to every possible *bundle*.
Before describing the bidding types, we need to define the concepts of **complementarity** and **substitutability**, already mentioned. **Definition**

Two disjoint sets S and T are called *complementar* if $v(S \cup T) >$

$v(S) + v(T)$, where v is a function that returns the evaluation a bidder give to the set, variable of the function. Conversely, two sets are called *substitutable* if $v(S \cup T) < v(S) + v(T)$.

The languages for the combinatorial auctions are usually done by (*atomic bids*), hence every bidder may submit only one bid, considered as pair *(B,p)*, where B is the *bundle* and p is the ask price.

The two most popular languages are:

(1). *additive-OR* (**OR**): can be proposed more atomic bids, knowing that every bidder can obtain any number of pairs;

(2). *exclusive-OR* (**XOR**): can be proposed more atomic bids, but the number of pairs to be obtained by the single bidder is at most one. In other words, the bidder obtains either all the *items* of the *bundle* listed in a specified bid, or nothing.

It is proved that the OR bids can represent all the bids that do not have substitutes; moreover, it is proved that the XOR bids can express all the types of bids.

The XOR language permits to every bidder to define a demand price for each possible winning combination. From this point of view, it can be considered the most suitable language for the combinatorial auctions. However, it has communicative and cognitive complexities caused by the exponential number of *bundles* to be evaluated.

1.3 Fields of application

In the literature concerning the combinatorial auctions numerous applications have been reported ([31]). For example, there are applications in the telecommunications, in *e-procurement*, in truckload transportation, in *supply chain*.

FCC spectrum allocations

FCC is the Federal Communications Commission, a federal agency in USA which allocates spectrum licenses. In these cases, the problem is to achieve an efficient, value maximizing, allocation of new spectrum licenses to wireless telephone companies. The mobility of clients leads to synergistic values across geographically consistent license areas; for example, the value for New York City, Philadelphia, and Washington DC might be expected to be much higher than the value of any one license by itself. Since some companies might value certain combination of licenses more than individual licenses, all the licenses have to be allocated at the same time.

Electronic procurement

The combinatorial auction can be used for procuring direct or indirect materials. A buyer wants to procure a *bundle*ofi *items* and sends a request for quote (RFQ) to several sellers. The vendors respond with quotes for subsets of *items*. The problem is to select the best set of bids that minimizes the total cost of procuring the required *bundle*.

This is one of the major application areas for combinatorial auctions since buying a bundle of items rather than individual items can reduce the times and lead to savings of the logistics costs.

Bandwidth exchanges

Public and private companies (sellers) get available slots of bandwidth of a fixed size and duration. Buyers (service providers or smaller companies) have values for bundles of slots. In this case, the allocation problem is to assign combinations of bandwidth slots to buyers and match them with sellers in order to maximize the total surplus in the system (that is the total amount received from the buyers minus the total cost to be paid to sellers). This problem leads to a combinatorial exchange.

Logistics and trasportation

Procuring logistics or transportation services is a natural application for combinatorial auctions since *bundling* is common and natural in logistics services.

A logistics exchange consists of *shippers* (buyers) who would like to ship *bundles* of loads from several sources to several destinations and *carriers* (sellers) who specify the cost of shipping along the bundles of routes serviced by them. Thus, a logistics exchange corresponds to a combinatorial exchange, too.

Supply chain formation

Automated, dynamic supply chain formation is currently an important problem and one of the approaches to solving this problem is based on combinatorial auctions. The agents here are the potential participants in the supply chain, placing bids on combinations of different resources in the supply chain. If the bidder does not get all components from the desired *bundle*, then the transaction has no value to him.

Distributed resources allocations

In a manufacturing plant, a set of jobs has to be scheduled across a set of machines. Each job has some deadline and possible cost of delay and requires to be processed on several machines. In this framework, the allocation problem is concerning how to select the best set of machine slots for individual jobs such that to minimize metrics like maximum tardiness or total delay, etc...

Another application is in collaborative planning. Consider a system of robots that wish to perform a set of tasks and have a joint aiml to perform the tasks at a cost as low as possible. Suppose there are n tasks to be performed and m robots are available. Each robot requires a certain cost for performing a subset of tasks. The overall goal is to allocate subsets of tasks to robots so as to minimize the overall cost. Many other resource allocation scenarios have been explored: for example, train scheduling, bus route allocation, airport time slot allocation, and airspace resource allocation.

Other applications

Recently, the combinatorial auctions have been used in improving school meals. Other interesting applications are in business to business negotiations, in spatial mission times assigning, in licenses to polution industries, in production planning, in space assigning to commercial televisions and in planning of travel packages. In the last case, the problem is to allocate flights, hotel rooms, and entertainment tickets to agents who have certain preferences over location, price, hotels, etc. Here, combinations are important because a hotel room without a flight ticket or an entertainment ticket has no value.

Chapter 2

Combinatorial Auctions for Truckload Procurement

Usually, auctions are considered in the context whereby human bidders compete with each other in order to purchase an item at the lowest possible price from an auctioneer who wants to sell the item at the highest possible price. In the case of allocation of transportation jobs, the auctioneer (e.g. a shipper) wants to subcontract transportation jobs at the lowest possible prices and each bidder (e.g. a carrier) wants to deliver the service at the highest possible payments. This situation creates a reverse auction because the sellers (carriers) bid instead of the buyers (shippers) and prices are bid down instead of up. The models for normal (forward) auctions can be obviously reversed and applied to reverse auctions.

2.1 Truckload Procurement

The truckload transportation includes *full truckload* (**TL**), *less-than-truckload* (**LTL**) and packages delivery. It has been the most important transportation area in U.S.A., producing in 2005 more than 739 mld dollars incomes, that is the $5,9\%$ of PIL. The trucking transportation represents over $84,3\%$ from the total worldwide transportation market incomes, only in U.S.A. represents by itself more than $40,6\%$([25]).

In TL transportation the goods are transported through dedicated movements from the **origin** (O) to the **destination** (D), without intermediar stops.

Shippers and **carriers** are the main actors in the TL market. The shippers can be producers, detailers, distributors or anyone needs to move the merchandise. The carriers are the transportation companies that have available tir, trucks or other .

In a TL contract the *lane* is represented by the auctioned item.

In practice, the general TL procurement process has five steps in the sequence of strategic, tactical and operational procedures.

Step 1. Carrier Screening: the procurement process begins with the strategic decision of selecting the carrier base. Shipper usually uses some kind of screening process in order to reduce the number of potential carriers to a reasonable subset. The most common screening criteria are the electronic data interchange capability, financial stability, the equipment availability and the geographic coverage. The aim of carrier screening is to reduce the complexity and cost of the final selection process, by filtering the thousands of candidate carriers down to hundreds or dozens of quality guaranteed carriers.

Step 2. Information Exchange: after selecting the set of potential carrier candidates, the shipper provides shipment network details to the carriers. These ones use the received information to develop bids for the procurement services and volume commitments. The information's quality and format that shippers communicate with the carriers are critical for the overall optimization of the procurement practice.

Step 3. Carrier Assignment: after having shared with the carriers the shipper's transportation requirement, depending on the bidding information the carriers submit, the shipper selects the final set of carriers that would best suit the procurement needs in terms of lowest cost. He assigns carriers to the shipment network for every traffic lane, hence a lane by lane assignment is performed either by a contract forming competitive bidding process or in the spot market. The contracts formed are usually open agreements between shipper and carriers, the load tendering carrier being picked for a lane at the time when the shipment is finally ready to be shipped. Step 2 and 3 are iterative and coupled as the tactical phase of the procurement process.

Step 4. Load Tendering: although carriers have been assigned to each lane during the Step 3, due to real time uncertainty, final choices need to be made for selecting exactly which carrier to use for each load as it becomes ready to ship. Hence, the assignment process provides only some guidelines as to which carrier to call for certain lanes but there is often need for real time choices to be made between alternative carriers.

Step 5. Performance Review: the final step of the procurement process is review of each carrier performance by tracking important Key Performance Indicator (carrier refusal rates, on-time pickup/delivery rates, service standard, etc...). This step provides feedback to the carrier screening procedure, suggesting corrective actions for the carrier screening decisions. Step 4 and 5 are seen as the operational phase of the procurement process.

One of the main problems in TL transportation is the *empty repositioning* because represents a significant part of the operative costs ([25]). An "'empty distance (repositioning)"' is called the situation when the vehicle travels unloaded. The *deadheads* are verified when a vehicle must come back to the depot or reach another destination in order to load the merchandise, when the drivers and the vehicles are not moving or for other reasons.

Since there are not payments for the empty repositioning and for the deadheads, it is necessary but not easy to search a set of loads that permit to reduce or eliminate them for the benefit both of the shippers and of the carriers.

Another important problem in TL transportation is the “valuation of the costs” done by the carrier. The movement costs of the merchandise on a lane are interdependent ([25]) because they are not determined only by the lane, but depend on the other lanes of the same loop (route), too. Therefore, the minimum cost to move the load on a lane will depend also on the volume of the other lanes.

Of particular interest in this thesis are the TL carriers which operate therefore over irregular routes like taxis, performing direct line-hauls from origins to destinations.

Because of very low fixed cost and sensitivity to the balance of the loads (empty repositioning is one of the major sources of cost for TL carriers), TL carriers tend to have slight diseconomies of scale and exhibit significant economies of scope ([4]). Economies of scope means here the total cost of a single carrier serving a set of loads is lower than that of multiple carriers serving the same set of loads. Since TL carriers show significant economies of scope, combinatorial auctions are effective auction mechanisms for shippers to procure TL transportation services.

The most common procurement process for transportation services is similar to a simple sealed-bid auction ([51]). Here an auctioneer (shipper) announces the bidding item (contract to serve a certain transportation job), a group of bidders (carriers) review this item, and then each of them submits a price in a sealed envelope. The auctioneer then reviews the bids and determines the winner.

2.2 Truckload procurement combinatorial auctions

The combinatorial auctions can provide more efficient allocations if they have a *multi-unit* structure and are useful mechanisms for the assigning of the loads, since the carriers may prefer some loads and hence bids without the fear to obtain an incomplete set of loads.

The shipper determines which loads to propose in the auction and the carrier has to know which *bundles* of loads to submit to the auctioneer. The auctioneer, that may be the shipper or an agent representing him, solves the *Winner Determination Problem* (WDP) in order to decide which bundles of loads to assign to the carriers. If we have a *one-shot* auction, after the solving of WDP there are no longer allowed bids. For iterative auctions instead, the carriers can submit again bids even after the winner determination, therefore at every iteration a new WDP is built and solved. These packages may be different from those of the previous rounds, depending on the new prices fixed by the auctioneer, called *ask prices*. Several stopping rules that finish the auction can be used.

2.2.1 Literature review

Helping the carriers to present efficient bids leads to a cost reduction even for the shipper ([25]).

An et al arrived at similar conclusions in [2]. Both the bidders and the shipper significantly benefit from the combinatorial auctions respect to the more traditional formats that allow bids only on single items. Hence, even the shippers have to encourage the use of the combinatorial bids.
Recently, big companies have started to experiment the use of the combinatorial auctions, wishing to give flexibility to carriers in the contracts

and to reduce the supplying costs.
In [22] it is reported the experience of *Sears Logistics Services* that, in 1995, was the first company that successfully used the combinatorial auctions for the transportation service assignment; in this way the *Sears* has saved mln of dollars per year from the transportation costs. The initial auction involved 854 loads with an effective cost of about 190 mln dollars yearly. Sears implemented an iterative combinatorial auction that riduced the cost to 165 mln dollars per year, a saving of 13%.
In [9] it is presented the experience of the *Home Depot* that, in January 2000, has used a *one-shot* combinatorial auction mechanism for the merchandise movement between its depots and the planning centers. The auctioned loads represented about 52.000 movements, that is a quarter of all the input movements in the stores of the Home Depot network. More than 110 carriers have been invited to participate and the major part of them submitted bids. In this auction the carriers had more freedom respect to the other traditional auctions of *Home Depot*; for example, the carriers could submit OR bids both on groups of lanes and on single lanes. Moreover, they could specify additional restrictions on the aggregated bids, that is a carrier could limit the number of loads assigned in a geographic area or, as default, the total number of lanes assigned to a carrier could not exceed his available capacity, etc... It has been said that "the new bidding process is a big success" and the "*Home Depot* intends to continue using this new bidding process", but there are not been reported the specific number of the savings. The auction had a big success: not only provided to *Home Depot* better costs, but many carriers had been satisfied of the lanes assigned to them.

The value of the combinatorial auctions for TL transportation is discussed in [5], where several optimization models for allowing the shipper to assign the lanes to carriers are presented. The experience of the authors (Caplice and Sheffi) in designing and lead more than 100 auctions for TL transportation, from which 50 were combinatoral, is reported.

These auctions involved more than 8 mld dollars in transportation services and have lead to a saving for the shippers of more than 500 mln dollars.
Sheffi refers in [50] that many other companies, besides *Sears* and *Home Depot*, like *Colgate-Palmolive*, *Compaq Computers*, *Ford Motors*, *International Paper*, *Lucent Technologies Inc.*, *Nestlè S.A.*, *Procter and Gumble*, *Quaker Oats* (a part of Pepsico Beverages and Foods Inc.) and the *Wal-Mart Stores*, have used the combinatorial auctions in order to decrease its transportation costs mantaining a high service level.
In [30] it is described the bidding approach for the *Reynolds Metals* based on optimization. Unfortunately, the model has not been completely implemented because of the limited functionality of the computers of that period.
The use of strategic tools for the assignment of lanes for the merchandise transportation becomes fundamental part of all the distribution chains. For example, *Manugistics Group Inc.* has bought *Digital Freight Exchange* in May 2002 in order to add bid submitting tools to the suite SRM. *Schneider Logistics* has introduced their module *Combined Value Auction* (CVA) in June 2002. The same authors worked to the development of the theory of combinatorial assignments in the transportation field ([4]) and in the application of optimization-based techniques for more than 50 companies in the TL transportation, LTL transportation, sea, railway and air transportation area. There were spent more than 8 mld dollars for the transportation services with a saving for the suppliers of about 500 mln dollars.

In [9] are described the combinatorial auctions in procurement. Making the "right" pricing decision is a complex task in sales or procurement. Pricing mechanisms in the exchange of goods/services are:

- posted price mechanisms (prices determined by seller; can be dynamic: customized prices or intertemporal prices);

- price discovery mechanisms (prices determined via a bidding process): auctions (forward or reverse).

In a reverse (procurement) auction the buyer puts out a request for quote (RFQ) for a service/product; prices are determined by a competition among potential sellers.

Combinatorial (package) auctions (CA), where bidders are allowed to submit bids on combinations of products or services, are effective mechanism since can lead to more economical allocations of products or services when there exist strong complementarities (synergies) over goods or services, with source varying for different bidders (see e.g., [43]). Prices are made on combinations of items (bundles or packages) and the bidders can submit multiple bids (a bid consists in the proposed bundle and its price). Combinatorial auctions empowered by the exponential growth of online procurement have recently received much attention in transportation and logistics industries. Internet auctions' benefits can be lower information, transaction and participation costs, increased convenience, ability for asynchronous bidding and access to larger markets.

Examples of companies using CA to procure logistics services are: Sears Logistics Services, The Home Depot; Walmart Stores, Compaq Computer Co., Staples Inc., The Limited Inc., Limited Logistics Services, Kmart Corporation (aided by Logistics.com)([9]). Sears Logistics Services in the early 1990s saved more than 84 million dollars by running six combinatorial auctions over a 3-year period ([22]). Limited Logistics Services saved 1.24 million dollars in 2001 compared to the previous year ([9]). It is noted that the TL trucking companies in the above-mentioned practical applications bid for fixed-term contracts instead of spot-market loads. Even if there are not spot-market combinatorial auctions in action now, there exists the believe that not only they should be, but even will be adopted and prevail in TL procurement auctions in the future ([6]).

Combinatorial auctions (CA) require bidding on an exponential number of bundles of loads (full economies of scope and scale), thus in [7] it is exploited the underlying structure of a truckload procurement problem in order to find solutions to fully-enumerated auctions in reasonable time.

Hence, this new approach in combinatorial truckload procurement auctions (CTPA) consist in the implicit consideration of complete set of all possible bids. Based on the paper of Beil, Cohn, Sinha (2007), there exists a known, amenable structure underlying the cost of servicing a given set of bid loads, then will be solved a minimum-cost flow problem in order to compute the least-cost (set of) tour(s) covering a set of loads. This research focuses on the complementarities among bid loads and carriers' existing networks and embed this underlying cost structure (bid generating function) directly into WDP, the resulting WDP being reformulated as multi-commodity flow (MCF) problem of polynomial size.

The contributions of the paper in [7] are:

- developed tractable models to solve a basic truckload procurement auction to optimality in single round, fully considering (implicitly) the exhaustive set of all possible bids;

- showed how the power of mathematical programming can enable this basic problem to be extended to include additional important real-world operational considerations;

- took advantage of this new capability to solve fully-enumerated truckload procurement auctions as a tool for conducting numerical analysis on the characteristics of CTPA solutions.

Carriers' cost structure consists of direct movement costs and indirect movement (repositioning) costs. The carriers try to build efficient continuous moves (tours) with minimal empty mileage, by combining bid loads, carrier's pre-existing contracted loads and opportunities on the spot market. These backhaul opportunities are uncertain at auction's time so carriers estimate them, for each directed city pair in the network, with an n-tiered step function (ehere 1 tier denotes 1 type of backhaul opportunity). Given the set of bid loads and the estimation of backhaul opportunities, the carriers determine the least-cost set of tours to serve these loads; this cost is used for computing the bid price (here, a first-price auction). As typically in a first-price auction, the bid price is given by the true-cost of the bid and a percentage-based markup ([52]).

In most of the CTPA papers the bundle prices are assumed exogenously endowed (external source) so there will be considered carriers' explicit prices for all the preferred bundles. In [7] the carriers compute the bundle prices using a well-structured *bid-generating function (BGF)* hence an implicit bidding approach to solve WDP using BGF directly, in lieu of the actual bids.

According to the traditional auction mechanism, the carriers compute the bid price for each bundle by solving a BGF, impossible in practice for CTPA with thousands of loads to compute prices and submit bids for exponential set of bundles and solve exponentially-large WDP. The solution given in [7] is that each carrier submits its BGF to auctioneer and these BGF are embedded into WDP. The resulting implicit WDP is a polynomially-sized model solution-equivalent to fully enumerated traditional WDP and can be reformulated as a multi-commodity flow (MCF) problem, easy solved in practice for CTPA ([1]). Moreover, the formulation is expanded to capture key operational considerations on the number of loads, number of winners, total mileage, favoring of incumbents, performance measures.

For a large-scale implicit WDP has been proposed an alternative model, largely invariant in increasing the number of loads (so appears a scalability improvement of orders of magnitude). The loads with common origin and destination cities are aggregated into a single lane with weight given by the number of loads on that lane.

The computational experiments done for CTPA with up to 200 bid loads have showed the scalability of implicit WDP and for CTPA with up to 5000 bid loads have showed the scalability and tractability of the alternative implicit WDP model (even extended with additional operational constraints).

A numerical analysis has been done in order to better understand the CTPA performance and characteristics (solution time, number of winners, empty movement percentages, etc...) and the effects on them of important problem parameters (number of carriers, number of loads, carriers' backhaul capacities, network structure, etc...).

In conclusion, the implicit bidding approach (proposed in [7]) has been applied to solve CTPA in a single round while implicitly considering the exhaustive set of all possible bundles. This approach directly addresses the two main challenges of the CA: bidding on an exponentially-large set of bundles and solving the corresponding exponentially-large WDP.

As future research interests, the authors of [7] address additional operational considerations: regional coverage requirements, backup carrier bids, and maximum tour length constraints; use the proposed tool to asses the quality of various auction mechanisms (first price, second price, etc) for truckload procurement or under various procurement settings; detailed modelling of uncertainties (in the cost parameters due to spot market variability, about carriers' existing and future networks, and timing effects) and development of appropriate solution approaches; extend the use of the implicit bidding approach to other application domains (wireless spectrum auctions, energy auctions, procurement auctions with capacity-constrained suppliers), after studying if the bid generating approach is amenable.

2.2.2 Difficult problems in Combinatorial auctions

In spite of the previously mentioned attractive characteristics, it is known that constructing desired bids and determining the winners in

CA pose a big burden on the bidders and auctioneers. For instance, if n products or services are posted, each bidder may submit bids for up to the theoretical $2^n - 1$ different combinations of goods or services. Thus, both the auctioneer's winner determination problem, and the bidder's bid construction and valuation problems are NP-hard ([53]). To solve the winner determination problem, some researchers have tried to develop efficient heuristic algorithms ([46]), while others have designed alternative auction mechanisms that restrict bidders to bid on the set of permitted combinatorial bids ([43]). These restricted approaches make the winner determination problem computationally manageable, but might reduce the value of CA because the bidders cannot perfectly express their synergistic values. Compared to the winner determination problem, the bid generation and valuation problems deserve much attention since are very important but not enough studied and for this reason are the focus of this thesis. Since, in practice, it is not always worthwhile to prepare all possible packages in many settings (e.g., truckload transportation procurement), a bidder needs only to submit necessary packages. Therefore, the techniques to extract desirable ones from a potentially huge number of possible bid packages are required ([6]). Challenging tasks in CA are:

- auctioneer's mechanism design problem;
- auctioneer's Winner Determination Problem (WDP): NP-complete ([32]);

  - exact optimal solution: fast search algorithms ([14]; [46]; [47]);

  - near-optimal solution: approximate solution methods ([38]; [14]; [21]).
- bidder' problem of preparing/submitting combinatorial bids (exponential number of bundles);
- bidders' problem of determining the appropriate bidding price on the bundles (considering own costs and resources and those of the

competitors).

Critical design questions are:

- restrict the number and the type of bids to submit ([32]) such that the WDP can be solved optimally in polynomial time; but bids' restrictions (no expression of bidders' preferences) yield economic inefficiencies like in non-CA ([43]);

- single round versus multiple round auction:

  - in single-round auction: famous Generalized Vickrey Auction (GVA) ([56] ; [21]) - bidders submit true valuations (truthful bidding) but over all possible bundles (resulting large and complex WDP for auctioneer);

  - in multiple rounds auction: the computational burden the single-round formats place on the bidders during the bid preparation process ([33], [34], [17]) is relieved. Thus bidders can submit bids on different bundles as prices change, make new bids in response to other agents' bids, submit bids on subsets of bundles in each round (if have limited or costly computational resources). Moreover, the auctioneer solves a sequence of smaller WDPs.

Chapter 3

The Bid Generation Problem

In this chapter is described the Bid Generation Problem (BGP) in TL transportation procurement combinatorial auctions, the focus of this thesis. After the presentation of the restricted literature regarding this problem, an original BGP model with synergistic chance constraints is described. Moreover, there are analyzed concepts like synergy, preprocessment of auctioned loads, distribution and independence of the random variables denoting clearing prices of loads component chosen bundle, etc...

3.1 Literature review

If the Winner Determination Problem was very much studied, there are only very few studies that focus on bid generation and evaluation problems.

In [2]it is proposed a model to assess bundle values given pairwise synergies and develop bundle creation algorithms for selecting profitable bundle bids based on the model. Their algorithms add as many profitable items as possible to a bundle given that the value of a bundle increases, on average, linearly in the bundle size.

In [53] it is proposed a two-phase strategy to solve a TL vehicle routing problem to generate bids. The first phase enumerates all routes satisfying routing constraints to generate candidate bid packages. The second phase associates a binary variable with each candidate bid package, and solves a set partitioning problem (bid construction problem) to determine desirable bids. Their bid construction problem assumes that all auctioned lanes must be served, and the objective is to minimize total operation empty movement cost.

As pointed out in [24], minimizing the total empty repositioning cost may not generate the right set of bid packages. They develop a TL vehicle routing model to maximize the profit in order to simultaneously, instead of sequentially such as that in [53], solve the route (package) generation and selection problems. In addition, their model allows auctioned lanes to be uncovered.

In [58] it is defined the first-order synergy as the complementarity between a set of auctioned lanes and a set of booked lanes, and second-order synergy as the complementarity between a pair of sets of auctioned lanes and booked lanes. They then demonstrate that the synergy of a bid package may depend on other packages that will be won. In addition, they define the profit-based optimality criterion for a combinatorial bid, and based on some specific assumptions, change the criterion into the cost-based optimality criterion. Based on the cost-based optimality criterion, they take the winning probability into account and show that the optimal solution to a vehicle routing problem may lead to inferior bid packages. Even though they make so much effort to define different synergies and demonstrate the drawback of employing vehicle routing models to generate bids, they eventually model their bid generation problem as a generic vehicle routing problem with time windows. The routing problem assumes that all auctioned lanes must be served, and the objective is to minimize the total transportation cost. Their elaborate definitions of different synergies are, however, not implemented in their bid generation problem.

In a combinatorial auction (CA), the exposure problem is avoided since a bidder can bid on bundles of items (reflecting thus his preference). In order to achieve efficiency, in the CA has to be addressed the Bid Generation Problem (BGP). Bidders have many different ways to bundle the items in a CA and the synergies between bundles usually depend on winning (or losing) other bundles. Therefore, the BGP in a CA is a significant and very complicated problem.

Bidding on transportation services offers a typical example of the BGP ([58]). Carriers bidding in bundles need to consider synergies of trucking routes and capacity.

The problem statements are:

- carrier fleet of homogeneous trucks with a depot;
- committed set of truckload shipments (engaged lanes);
- call for bids on a set of truckload movements (lanes);
- each lane (engaged or not) has an origin, a destination and a pickup time window;
- the service network is fully connected.

The carrier has to generate a set of combinations of freight lanes to cover the lanes in auction and maximize its profit from the auction. The objective is to minimize the total expected empty travel distance. The combinations are of the OR type, that is any subset of a bid can be won in the auction outcome.

Definitions:

Bid: a set of combinations (that form a partition of the set of auctioned lanes) submitted by the carrier;

Derived bid: a set of combinations made up of the original combinations;

Outcome set of a bid: set of all the possible auction outcomes (combinations won by the carrier) of that bid;

First-order synergy: measures the complementarity between a set of lanes and the engaged lanes;

Second-order synergy: represents the complementarity between a pair of sets of lanes and the engaged lane (might be negative).

Optimal combinatorial bid: maximizes the expected profit (revenue of the outcomes of that bid minus related cost empty travel distance); the formula (optimality criterion) is valid for XOR and OR bids.

Evaluation of a bid: need to know probability, revenue and cost for each outcome.

Remark:

In a CA, the cost can be accurately evaluated only when an outcome is realized (using an optimal fleet allocation algorithm to solve the problem of assigning trucks to unserved lanes to minimize the total empty travel distance). Ex ante (without knowing the exact outcome), it is difficult to generate a combinatorial bid (bundling the items) to achieve the minimal empty distance travelled ex post.

Assumptions:

- competitive market (carriers bid for transportation service procurement);
- bidders price their bid using a value pricing scheme (prices are set based on the market value of each lane); the price for a combination is the sum of market prices for each individual lane included and is independent of the combinations made;
- all the outcomes have the same probability (in deregulated market: competition equally likely everywhere);
- only OR bids examined: each lane in a bid has the same winning probability and each lane among different bids must have the same winning probability;
- the winning probability of each lane is independent of what other lanes are in the same bundle;
- any bidding strategy a carrier adopts could well be used by its competitors and the bidders in the market are equally competitive (reasonable approximation of the transportation markets, with multiple carriers often

maintaining an equally intensive service network);

Remarks:

1). Using the optimal fleet assignment solution may not be the optimal bundling strategy (i.e. doesn't necessarily lead to the optimal bid, by grouping the lanes assigned to the same vehicle), hence is identified a sufficiency condition for the optimal OR bid.

2). When engaged lanes are not present and when the lanes can be grouped into geographically isolated combinations that meet sufficiency conditions, it is optimal to take each group as a combination.

3). Multiplicity of optimal bid: when an OR bid satisfying sufficiency condition is optimal, its derived OR bid is also an optimal bid (under that condition).

Two heuristic methods are proposed for generating combinatorial bids.

The first heuristic, based on a fleet assignment model, give a generic formulation for the routing and scheduling problem and solve it; group the lanes assigned to the same vehicle into one combination then the resulting bid consists of all the combinations.

The second heuristic, based on the nearest insertion method, have as the basic idea to insert a lane into an assignment for any vehicle that minimizes the total empty travel distance and do this to all lanes, one by one, until they are all assigned. It is realized the construction of heuristic assignment and the generation of combinatorial bids is done like in the first heuristic. Heuristic 1 is computationally complicated, whereas Heuristic 2 is easy to implement.

Numerical experiments for comparing the performances of the two heuristics show that, on average, the simple nearest insertion heuristic underperforms the integer programming-based optimal fleet assignment model in most instances, but it may outperform the latter by up to 8% in some instances and by 5% (in terms of the total expected empty distance travelled) in many other instances; by contrast, in a routing and scheduling problem, the former always underperforms the latter. Winning probability and engaged lanes have an unclear effect on the relative performance of the two heuristic bidding methods.

In conclusion, although most users prefer to use the formulation of the Heuristic method 1, as indicated in [51], the optimal fleet assignment model does not necessarily lead to the best solution (see Remark 1 above). Considering the effect of the stochastic factors in demand, time, etc... the authors cautiously suggest just the nearest insertion method for the BGP if the implementation of the optimal fleet assignment algorithm implies large cost or technical difficulty. Although pricing is an integral part of bid generation, it is shown that bundle pricing is separable from bundle generation in this application, bundle generation problem being discussed in this paper and bundle pricing will be topic of the future research of the authors.

In [24], the carrier's optimal Bid Generation Problem (BGP) in truckload transportation procurement combinatorial auctions is studied. The authors propose a carrier optimization model in which the simultaneous generation and selection of routes are integrated and existing lane commitments are also incorporated together with total capacity and other operational constraints (trucks must return the original depot and driving distance limitation). Carriers (bidders in this auction) use VRP models in order to identify sets of lanes (based on the actual routes of his own fleet of trucks) that will maximize his profit. Thus, the objective of the carrier optimization model is to maximize the utility defined as the difference between the revenue from servicing a set of lanes (origin-destination pairs) and the transportation costs (physical costs of corresponding route). Given prices for lanes, the model selects only the best package (set of lanes) to submit to the shipper (auctioneer), that is the package offering the most profit to the carrier and not that one achieving the least repositioning cost (amount of empty movement) as in other papers ([51]). This is explained by the goal: find the optimal trade off between the rewards obtained from servicing a set of lanes and the associated repositioning costs of the vehicles. The model is a nonlinear integer program (both the objective function and some constraints are quadratic), which is solved by using a decomposition approach based on column generation and Lagrangian relaxation, then a decomposition based heuristic is developed. The decomposition strategy involves a partition of the model into a master problem and a sub problem for which a column generation-like strategy is employed to derive approximate solutions to the original carrier formulation. In the case of single round auctions, reservation prices for lanes can be used as coefficients in the utility maximization (objective function). Since bidders involved in transportation procurement combinatorial auctions have hard computational tasks to evaluate potential packages of lanes, a multi-round format would be an ideal framework in which bidders could employ optimization to further ameliorate the computational challenges and can use current price information for packages to make adjustments in strategies. Furthermore, prices for individual lanes (corresponding to revenue received for servicing a lane) could be used as well in multi-round transportation procurement combinatorial auctions ([18]) as coefficients in the objective function of a carrier's bid generation optimization to determine the best package. The model can be incorporated in multi-round settings (but still has to be validated), by using marginal approximate-price information for lanes based on tentative allocation of lanes in a round ([18]). For computational experiments have been considered instances for carrier models with up to 335 lanes and have been observed that the proposed decomposition algorithm effectively computes optimal solutions up to 200 lanes. The model presented in this paper pertains to a single depot of the carrier in order to capture realistic features of driver and equipment re-origination (both, but especially the drivers, often must return to the same physical location, the depot). If there are more depots, the authors suggest that the optimization formulation can be used separately for each depot (since each depot problem is responsible for lanes around a certain distance away from the depot, which is realistic in practice). The carrier solves his bid generation model (for each depot) and then he could amalgamate all of the resulting bids from the different depots into an OR bid to submit to the shipper. An alternative approach suggested in the paper is to model the carrier's BGP with multiple depots in a single formulation, but the computational complexity would obviously increase. Thus, the decomposition strategy (decomposition of lane responsibility per depot), seems to be a more tractable alternative, especially for situations involving thousands of lanes to be served by a carrier. Besides validating the carrier model proposed in this paper in a multi-round setting, another aspects for authors' future research (important issues in real world truckload combinatorial auctions, also) consists in the incorporation of win/loss probabilities for lanes and in including the uncertainty in the actual volume (that will realize) for a given lane.

In [53], the authors investigate the bidding problem in the context of freight transportation contract procurement combinatorial auctions from a carrier's (bidder) perspective, that is they examine the problem of constructing sets of bids in such auctions so as to optimize the efficiency of the auction from the perspective of an individual bidder. The bid valuation and construction problem for carriers in combinatorial auctions for the procurement of contracts for freight transportation services is very difficult and involves the computation (solving) of a number of NP-hard sub problems. Besides the complexity of this problem ([33]), is also noticed the actual lack of bidding decision support tool for carrier's operations. Thus, computationally efficient approximation methods for estimating the carriers' true values and constructing bids are proposed in this paper. The authors use the same notations and definitions as in [52], such as atomic bids, carrier's true cost of serving a set of new lanes, complementary, substitutable or additive sets of lanes, bidding language,etc... All this because this paper includes a great part of the above mentioned paper (the Bid Construction problem in the absence of pre-existing commitments). A lot of assumptions are made, such as TL case, the absence of a central depot and the unlimited carrier's capacity, the type of one-shot first-price reverse auction, the carriers bid truthfully and do not take into account the competitors' behaviour. The Bid Construction Problem (BCP) in combinatorial auctions for the procurement for freight transportation contracts is studied in two different scenarios: in the absence of pre-existing commitments and in the presence of pre-existing commitments. Optimization-based approximation algorithms for solving the above problem in each scenario are also proposed. For the first scenario, carriers either do not have any precommitted contracts of current lanes, or they do not intend to integrate new lanes into their current operations; therefore, they are only interested in the combination opportunities among new lanes. Thus, carrier preferences can be expressed with OR bids, reducing the complexity of WDP. The main idea of the proposed strategy to generate bids is that the carrier construct bids such that the total operating empty movement cost is minimized . Since this requires solving a TL VRP, the authors follow an approach similar to that one of solving VRP: set partitioning (SP) formulation of the problem and column generation method for exact solutions. The first step of the bidding strategy consists in using a search algorithm (depth first search algorithm) to enumerate all routes with respect to routing constraints () and treat each route (candidate bid) as a decision variable in the SP formulation of the BCP (BCP-SP). The new lanes in this route form the set of items bid, its reservation cost determines the bid price and can be calculated, as in [52], on the base of route length, empty movement cost and carriers' profit margin. Each new lane is duplicate hence it can be used as empty lane by other routes. The number of optimal routes may exceed the carrier's fleet capacity, but one can restrict the number of selected routes less than or equal to the carrier's fleet size. In BCP-SP is imposed the constraint that each lane is covered only by one optimal bid (two optimal bids are mutually exclusive of new lanes). In order to explore all the bidding opportunities for substitutable bids, the above set of constraints is relaxed in the BCP-SP formulation, remodelling it as a Set Covering problem (BCP-SC). To solve it the authors propose the use of a modified Branch and Bound algorithm that search until all optimal solutions are found. Moreover, for substitutable bids, is used the Bid Set Augmentation Rule in order to detect additional bidding opportunities. For the second scenario, the previous bid construction strategy is extended to the situation in which carriers already have commitments to other contracts prior to the auction (carriers may have contracts serving multiple customers). Carriers will not only deliberate on their bidding plans (on the base of combinational opportunities among new lanes) but also will have integrate these new lanes into their current operations. In this case, there will be generated more candidate routes, in addition to those bids generated in the first scenario including those bids combination of current and/or new lanes and/or empty lanes. Now, not only new lanes are duplicated, but also current (existing) lanes. Besides the constraints in BCP-SC that each new lane is covered by at least one bid, there are the constraints that guarantees the inclusion of current lanes in certain routes. Moreover, XOR bids are developed for any two atomic bids that have substitutable valuations with respect to a common set of current lanes. Finally, the bids that conflict with pre-existing routing plans are identified and excluded by using the Bid Substitution Condition. The performance of the proposed bid construction method respect to complete enumeration was studied by using a simulation-based experiment. The number of atomic bids generated by the above method (for the two scenarios) is significantly fewer than that of complete enumeration and thus, it is much faster than the complete enumeration method in terms of computation time. The quality of the bids constructed by the new method is quite close to that of the complete enumeration method; the performance of the proposed method in terms of number of new lanes won by each of the carriers (”Smart” or Enumeration) and the empty movement costs after auction is quite good. The optimization-based bid construction strategy presented in this paper results optimal for carriers in terms of operational efficiency in the absence of pre-existing commitments and near optimal when pre-existing commitments are also considered. Moreover, the benefit of the approximation method proposed is that it provides a way for carriers to discover their true costs and construct optimal or near optimal bids by solving a single NP-hard problem, so a significant improvement in computational efficiency. Future research extensions of this paper can include application of the proposed bidding methodology to broader fields with properties among bid items similar to that in the transportation contract procurement combinatorial auctions, explicit consideration of the stochasticity of demand and supply, considering multi-attribute contracts, multiple and divisible units (truckloads) on each lane, examine the BCP in a dynamic auction.

The research in [2] investigates in what consist a ”good bidding strategy”, trying to answer the critical question ”How bidders should bid in combinatorial auctions (CA) since evaluating and submitting all possible bundles is not practical for the bidders and the auctioneer?”.

In CA a bidder can express his synergies among items by submitting bids on bundles of goods, so CA are commonly used for allocating complementary resources.

Definition:

Two items are *complements* (exhibit synergies) when their combined value is larger than the sum of their independent values.

Example:

the lanes in a transportation network may be complements if a group of lanes (geographically close or forming continuous routes) can lead to higher efficiency for a carrier.

The contributions of the paper in [2] are:

- Proposes a simple and efficient model for evaluating the value of any bundle, given pair wise synergies (limited information);
- Designs bidding strategies that efficiently identify desirable bundles;
- Evaluates (via simulations) the performance of different bundling strategies under various market settings;
- Answers questions like: how does the auctioneer's revenue change as more bidders submit bundle bids, how are revenues distributed among bidders in CA versus non-CA, what issues should bidders consider when generating and pricing bundles under various market environments.

It is focused on single-round, first price, sealed-bid forward CA in the transportation industry.

The synergy model proposed in [2] has as input the item values and pairwise synergy values and as output the bundle values for any combinations (key input for any bidding decision support tool for CA).

The bundle value is given by the sum of the values of the individual items in the bundle and the 'synergy' values among the items in the bundle. Hence, the bundle value is:

- the item value (for a singleton bid);

- the sum of the two items values plus the pairwise synergy value between them (for a doubleton bid);

- the product of bundle's cardinality and its *average unit contribution* AC (equals to the sum of the average individual of items in bundle and the average pairwise synergy of items in bundle), for a bundle with size greater than 2 Since we have a very efficient computation $O(n^2)$, with n the number of items auctioned and the bundle value increases linearly in bundle size, this model would be appropriate in transportation auctions, where both small and large bundles could be valuable for the bidders ([37]). But real data from CA are generally not publicly available and for this reason the model is not tested or validated.

Bidders in transportation auctions commonly use some ad hoc bidding strategies:

- submit only singleton bids;

- bid on high value packages;

- take competition into account when generating bundles;

- combine a very attractive lane with less desirable lanes,

- put together lanes that increase the 'density' in an area.

The study in [2] proposes 3 *bundling strategies*:

- one naive strategy (bidders don't submit any package bids);

- two wise strategies (internal-based strategy, INT, and competition-based strategy, COMP).

The bidding strategies focus on generating bundles, not on pricing , since it is assumed that bidders price their bundles using a fixed profit margin.

The *internal-based strategy, INT* focuses on identifying bundles with comparably high average value per item. As example in TL CA, the carriers submit package bids based on the relative value of the shipper's lanes to their network rather than the competitors' networks ([37]). The bundle creation algorithm starts from each individual item and searches for items to add in order to increase the most the current bundle's AC, process repeated until AC cannot be increased, so will be generated at least n 'desirable' bundles with $O(n^3)$ running time.

The *competition-based strategy, COMP* focuses on identifying bundles for which a bidder has a relatively high valuation compared with his competitors. Similar to INT, except the criterion for adding an item to a bundle is the value ratio (VR) of a bidder for a bundle (instead AC), hence there will be incorporated in the model only the competitors' item values, not their synergy values (in practice, more difficult to gain information on them). As example in TL CA, the values for individual lanes are very much dependent on the cost of operating a truck (uniform across different companies, depending on fuel cost and driver salaries); the cost of operating a truck on a group of lanes (package bid) depends not only on lanes but also on carrier's current network (private information to carrier, difficult to acquire by competitors).

Simulation experiments (for trucking and spectrum auctions, items associated with geographic locations, different types of bidders in size and valuations) have been made to test the performance of the proposed bundling strategies and answer questions. Simulation assumptions are 4 regions, 20 items (5 per region), the maximum number of bundle bids (NB) per bidder limited to 2,5,10,15,25. There is no restriction on the number of singleton bids (submitted for all items); all bidders of the same type use the same bundling strategy and the same profit margin (equal to 0).

There are 2 models: market environments with different-size bidders with comparable valuations (Model 1) and same-size bidders with asymmetric valuations (Model 2).

Model 1 uses 21 bidders of 3 types: local, regional and global, and different distributions to model bidders' synergy values.

Remarks:

1. The auctioneer's revenue (directly proportional to the sum of the values of winning bids) increases (due to inclusion of synergies in bundle bids) in the number of types of wise bidders and NB.

2. In general, for the auctioneer the benefit of adding a type of wise bidder is greater than the benefit of increasing NB (prefers educate bidders to bid wise than solve large WDP).

3. Bundle selection for submission in decreasing order of AC (for INT) and VR (for COMP); for global bidders INT and COMP generate overlapping bundles: Restricted Overlapping Frequency (ROF) restricts

the degree of overlap across submitted bundles so the modified bundle selection procedure in order not to violate the ROF for any item is used, hence a revised INT (COMP) strategy is also proposed.

4. When only the global bidders are wise it is best for them to submit bundles with a moderate degree of overlap (more variety implies higher revenues); when all bidders are wise ROF should not be a constraining factor in the bundle selection process for global bidders.

5. Global and regional bidders, in general, win more items via bundle bids and earn higher revenues with COMP, while local bidders win more items via bundle bids and earn higher revenues with INT.

In practice, bidders use different profit margins for pricing bundles ([4]; [37]). Experiments various scenarios with 1 test bidder with profit margins values varying from 0.01 to 0.10, remaining bidders' profit margins fixed to 0.05. The ratio of optimal profit margin and threshold profit margin is the risk measure (RM).

Remarks:

6. RM is larger in CA than in non-CA for all bidder types.

7. Local and regional bidders have a larger RM than do global bidders in CA.

8. Local bidders do not need to bid more aggressively than regional and global bidders.

Model 2 make experiments with 10 global bidders and the bidders' synergy values comes from the same distribution, but there are asymmetries in their item valuations (symmetric bidders draw valuations for all regions from the same distribution, asymmetric bidders from different distributions for different regions).

Remarks:

Remarks 1. and 2. still hold under Model 2.

9. Symmetric bidders prefer INT and asymmetric bidders prefer COMP.

In order to compare the bundling strategies INT and COMP with the full enumeration, there have been made experiments with 10 items , 2 regions, 6 local bidders and 3 global bidders.

All bidders use the same bundling strategy except 1 test bidder using either the same strategy as the other bidders or full enumeration; bidders submit all generated bundles. For a relatively small percentage of profit loss in most of the 25 instances, the proposed bundling strategies offer significant computational advantage to the bidders (20 bundles generated instead 1023 by full enumeration). An auctioneer facing bidders who strategically submit bundles, rather than submit bids on all possible bundles, gains significant computational advantages in return for a small loss in profits.

In conclusion, in [2], a simple and efficient model has been proposed for evaluating bundle values given pairwise synergies and bundling strategies developed to help bidders select promising and profitable bundle bids; the efficiency and the performance of bundling strategies has been tested under different market environments using simulations; experimental results show large benefits for both bidders and auctioneer from bundle bids and interesting insights were gained; there have been provided to bidders some suggestions when selecting and pricing bundles.

3.2 Combinatorial Auctions for Truckload Procurement: the Bid Generation Problem with Chance Constraints

The purpose of our study is to design a *bidding advisor* to help TL carriers made bidding decisions in a single-round, one-sided, sealed-bid, first-price combinatorial auction for spot-market loads. The TL carrier will apply the bidding advisor to generate desirable bids and their associated prices by solving the embedded *bid generation and pricing problems*, based on the currently known information within the planning horizon (1 week in our case).

The known information:

- number and location of vehicles (assuming all vehicles available for the first time at the beginning of the planning horizon);
- booked and auctioned loads (pickup and delivery locations, pickup/delivery time window).

The revenue of pulling a load is defined as follows:

- each booked load has a known revenue;

- for an auctioned load the revenue is defined (possibly) within the bundle representing the bid (not individually).

The price of the bid is a decision variable in our problem. Since now, only Savelsbergh in [54] consider the price as a variable and not as a parameter (fixed equal to the asked price of the auctioneer) like in all the existing other studies. For those existing papers who model the bid generation problems as vehicle routing problems, only one allows auctioned items to be uncovered. The assumption that all auctioned items must be covered may generate inferior bids due to neglecting the TL carrier's current fleet management plan. Although the aforementioned facts are neglected in the combinatorial TL auction literature, they have been considered in some single-item TL auction studies (a special case of the combinatorial TL auction: [11], [12]). Therefore, in truckload procurement, the bid generation problem is better formulated as time'space network based fleet management problems (see e.g., Powell et al., 1995) instead of vehicle routing problems. For the above reason, in determining the auctioned lanes the carrier has to consider its fleet management plans and consequently, bid on a bundle of loads that fit as much as possible into its plans. Thus, our proposed bidding advisor tightly integrates the load information in e-marketplaces with TL carriers' current management plans. Therefore, it can help TL carriers make effective bidding decisions. It will be proposed only one bundle, (with its price and the corresponding routing), that the carrier is confident to win and that maximizes the carrier's profit.

It is obvious that the core components of the bidding advisor are the embedded bid generation and pricing problems.

In our study, the TL carrier's bid generation and pricing problems in one-shot combinatorial auctions are formulated as a synergistic minimum cost flow problem (instead of a vehicle routing problem, as usually in the literature). The network flow problem takes into account all the above mentioned crucial characteristics of the bid pricing and generation problems.

Problem definition:

Let $G = (V, A)$ be a directed complete graph, with V the set of cities and A the set of all possible links (roads) between cities.

The bid generation and evaluation problem is formulated in a time-space network where the planning horizon T (1 week) is divided into discrete intervals (days).

Notation:

L_0 - set of loads (carrier's existing network)

L - set of loads being auctioned

$B = \wp(L)$ - set of considered bundles of loads

Y_b - random variable: clearing price for bundle b

K - set of trucks of the carrier

$\alpha \in [0, 1]$ - confidence level

c_{ij} - cost of the arc (i, j)

τ_{ij} - travel time between nodes $i \in V$ and $j \in V$ (assume $\tau_{ii} = 1$)

$R(L_0)$ - revenue from the booked loads

a_i^k is 1 if truck k is in node i at the beginning of the time period, 0 otherwise

For any load $l \in L \cup L_0$:

$i(l)/j(l)$ origin/destination of load l

$a(l)/b(l)$ starting time/end time for pick-up/delivery time window at $i(l)/j(l)$

Variables:

y_{ij}^{kt} binary variable: truck k is moving or not from i to j starting at time t

p_b continuous variable: bidding price for bundle b

x_b binary variable: is 1 if the carrier bids on bundle b, 0 otherwise.

THE MODEL and its VARIANTS

MODEL (pick-up time windows):

$$\max(\sum_{b\in B} p_b x_b + R(L_0)) - \sum_{k\in K}\sum_{(i,j)\in A}\sum_{t=1}^{T-\tau_{ij}} c_{ij} y_{ij}^{kt} \qquad (1)$$

s.t.

$$P(p_b x_b \leq Y_b) \geq 1-\alpha \qquad \forall b \in B \qquad (2)$$

$$\sum_{b\in B} x_b \leq 1 \qquad (3)$$

$$\sum_{j\in V} y_{ij}^{k1} = a_i^k \qquad \forall i \in V, \qquad \forall k \in K \qquad (4)$$

$$\sum_{j\in V: t+\tau_{ij}<T} y_{ij}^{kt} = \sum_{j\in V: t-\tau_{ji}\geq 1} y_{ji}^{kt} \qquad \forall i \in V, \qquad \forall t > 1, \qquad \forall k \in K \qquad (5)$$

$$\sum_{k\in K}\sum_{t\in[a(l),b(l)]} y_{i(l)j(l)}^{kt} \geq 1 \qquad \forall l \in L_0 \qquad (6)$$

$$\sum_{k\in K}\sum_{t\in[a(l),b(l)]} y_{i(l)j(l)}^{kt} \geq x_b \qquad \forall b \in B, \qquad \forall l \in b \setminus L_0 \qquad (7)$$

$$\sum_{k\in K}\sum_{t\in[a(l),b(l)]} y_{i(l)j(l)}^{kt} \geq 2x_b \qquad \forall b \in B, \qquad \forall l \in b \cap L_0 \qquad (8)$$

$$y_{ij}^{kt} \in \{0,1\} \qquad \forall i \in V, \qquad \forall j \in V, \qquad \forall k, \qquad \forall t \qquad (9)$$

$$x_b \in \{0,1\}, p_b \geq 0 \qquad \forall b \in B \tag{10}$$

The objective function (1) maximizes the profit defined as the difference between revenues (deriving from booked loads plus auctioned loads) and total cost of the routing. Probabilistic constraints (2) impose a minimum reliability of α for a bid to be submitted with the winning price. Both (1) and (2) can be easily linearized. Constraint (3) will force the model to choose only one bundle (the most convenient one). Constraints (4) gives information on the location of the trucks at the beginning of the planning horizon. Constraints (5) are the balance constraints. Constraints (6) will force the model to serve all the booked loads within the pre-specified time window, Constraints (7) and (8) represent the relationship between the routing variables and the bid selection variables. Only the auctioned loads that belong to the bundle should be served within its time window. Finally, constraints (9) and (10) are the domain definition for the variables.

MODEL (delivery time windows):

$$\max(\sum_{b \in B} p_b x_b + R(L_0)) - \sum_{k \in K} \sum_{(i,j) \in A} \sum_{t=1+\tau_{ij}}^{T} c_{ij} y_{ij}^{kt} \tag{1}$$

s.t.

$$P(p_b x_b \leq Y_b) \geq 1 - \alpha \qquad \forall b \in B \tag{2}$$

$$\sum_{b \in B} x_b \leq 1 \tag{3}$$

$$\sum_{j \in V} y_{ij}^{k(1+\tau_{ij})} = a_i^k \qquad \forall i \in V, \qquad \forall k \in K \tag{4}$$

$$\sum_{j \in V: t+\tau_{ij} \leq T} y_{ij}^{k(t+\tau_{ij})} = \sum_{j \in V: t-\tau_{ji} \geq 1} y_{ji}^{kt} \qquad \forall i \in V, \qquad \forall t > 1, \qquad \forall k \in K \tag{5}$$

$$\sum_{k \in K} \sum_{t \in [a(l), b(l)]} y_{i(l)j(l)}^{kt} \geq 1 \qquad \forall l \in L_0 \tag{6}$$

$$\sum_{k\in K}\sum_{t\in[a(l),b(l)]} y^{kt}_{i(l)j(l)} \geq x_b \qquad \forall b\in B, \qquad \forall l\in b\setminus L_0 \qquad (7)$$

$$\sum_{k\in K}\sum_{t\in[a(l),b(l)]} y^{kt}_{i(l)j(l)} \geq 2x_b \qquad \forall b\in B, \qquad \forall l\in b\cap L_0 \qquad (8)$$

$$y^{kt}_{ij} \in \{0,1\} \qquad \forall i\in V, \qquad \forall j\in V, \qquad \forall k, \qquad \forall t \qquad (9)$$

$$x_b \in \{0,1\}, p_b \geq 0 \qquad \forall b\in B \qquad (10)$$

EXAMPLE: Let consider the case a carrier has a fleet of 3 vehicles serving, in 7 cities (regions), 5 already booked loads and (possibly) 5 auctioned loads within one week. Thus, $V = \{1,2,3,4,5,6,7\}$, $L = \{(4,5),(6,1),(2,5),(4,3),(7,4)\}$, $L_0 = \{(1,2),(4,3),(6,3),(6,7),(5,1)\}$.

The 3 trucks available are distributed in the 7 cities as following: tr1 is in the node 1, tr2 is in the node 4, tr3 is in node 6.

The travel times betweens cities are given by the matrix:

$$\tau = \begin{pmatrix} 1 & 1 & 1 & 2 & 2 & 3 & 1 \\ 1 & 1 & 2 & 1 & 1 & 2 & 2 \\ 1 & 2 & 1 & 2 & 1 & 1 & 1 \\ 2 & 1 & 2 & 1 & 2 & 3 & 1 \\ 2 & 1 & 1 & 2 & 1 & 1 & 1 \\ 3 & 2 & 1 & 3 & 1 & 1 & 2 \\ 1 & 2 & 1 & 1 & 1 & 2 & 1 \end{pmatrix}$$

The costs of traveling betweens cities are given by:

$$C = \begin{pmatrix} 0 & 289 & 283 & 587 & 607 & 906 & 268 \\ 289 & 0 & 618 & 293 & 278 & 558 & 542 \\ 283 & 618 & 0 & 527 & 275 & 261 & 290 \\ 587 & 293 & 527 & 0 & 575 & 909 & 286 \\ 607 & 278 & 275 & 575 & 0 & 271 & 289 \\ 906 & 558 & 261 & 909 & 271 & 0 & 615 \\ 268 & 542 & 290 & 286 & 289 & 615 & 0 \end{pmatrix}$$

The time windows for the loads of L are $\{[2,3],[4,4],[3,4],[5,6],[3,4]\}$; the time windows for the loads of L_0 are $\{[3,5],[7,7],[7,7],[3,5],[5,7]\}$.

The random variable Y_b is given by $\sum_{l\in b} X_l * syn(b)$, where X_l are random variables denoting the clearing price of each load l and are distributed $\mathcal{N}(\mu_l, \sigma_l)$. We consider X_l independent, $\mu_l = M_l$ (M_l is the asked price for load l) and $\sigma_l = 3\% M_l$.

Thus, Y_b is distributed $\mathcal{N}(\mu_b, \sigma_b)$, with $\mu_b = \sum_{l\in b} \mu_l * syn(b)$ and $\sigma_b = \sqrt{\sum_{l\in b} \sigma_l} * syn(b)$.

The asked prices (auctioneer) for the loads of L are: $(792, 1170, 395, 652, 389)$.

The synergy (syn_b) between loads of the possible bundles (31) and existing network is computed and given by:

1.00	1.00	0.94	1.00	0.97	0.95	0.96	1.00	0.96	0.93	
0.96	0.96	0.97	0.96	0.96	1.00	0.93	0.94	0.94	0.98	
0.96	0.97	0.96	0.96	0.95	0.96	0.96	0.97	0.97	0.97	0.97

The model, linearized and with the chance constraint (2) rewritten according to the given distribution, is the following:

$$\max(\sum_{b\in B} p_b + R(L_0)) - \sum_{k\in K} \sum_{(i,j)\in A} \sum_{t=1}^{T-\tau_{ij}} c_{ij} y_{ij}^{kt} \tag{1}$$

s.t.

$$p_b \leq (\alpha\sigma_b + \mu_b)x_b \qquad \forall b \in B \tag{2}$$

$$\sum_{b\in B} x_b \leq 1 \tag{3}$$

$$\sum_{j\in V} y_{ij}^{k1} = a_i^k \qquad \forall i \in V, \qquad \forall k \in K \tag{4}$$

$$\sum_{j\in V: t+\tau_{ij}<T} y_{ij}^{kt} = \sum_{j\in V: t-\tau_{ji}\geq 1} y_{ji}^{kt} \qquad \forall i \in V, \qquad \forall t > 1, \qquad \forall k \in K \tag{5}$$

$$\sum_{k\in K} \sum_{t\in[a(l),b(l)]} y_{i(l)j(l)}^{kt} \geq 1 \qquad \forall l \in L_0 \tag{6}$$

$$\sum_{k\in K} \sum_{t\in[a(l),b(l)]} y_{i(l)j(l)}^{kt} \geq x_b \qquad \forall b \in B, \qquad \forall l \in b \setminus L_0 \tag{7}$$

$$\sum_{k\in K}\sum_{t\in[a(l),b(l)]} y^{kt}_{i(l)j(l)} \geq 2x_b \qquad \forall b \in B, \qquad \forall l \in b \cap L_0 \qquad (8)$$

$$y^{kt}_{ij} \in \{0,1\} \qquad \forall i \in V, \qquad \forall j \in V, \qquad \forall k, \qquad \forall t \qquad (9)$$

$$x_b \in \{0,1\}, p_b \geq 0 \qquad \forall b \in B \qquad (10)$$

The model is implemented in GAMS. After the execution (with the input data given above) we have that the carrier chooses to propose in the auction the bundle 26 consisting of the loads $(4,5),(2,5),(7,4)$ at the price of 1467, obtaining the profit of 1399.

Detailed results are given in the related file .lst.

Modifying the model

- modifying the constraints:

Case 1). If we want to modify the constraint (3) in order to impose that the maximum number of bundles of loads the carrier may propose is more than 1, we will have that the proposed bundles may have loads in common (are not disjoint). However, the maximum number the carrier can propose (including the single-load bundles) is $2^{|Bundle1|} - 1$, where $Bundle1$ is the bundle chosen with constraint (3) not modified.

For the previous example, if the constraint (3) becomes

$$\sum_{b\in B} x_b \leq 3 \qquad (3')$$

then the carrier will propose the bundles 10, 24 and 26 consisting of $\{(4,5),(2,5)\}$, $\{(4,5),(7,4)\}$ and $\{(4,5),(2,5),(7,4)\}$, respectively, at the prices of 1062, 1091 and 1467, respectively, obtaining of course a greater profit (3552). But this is a false profit, because the carrier will never win simultaneously the 3 not disjoint bundles!

Case 2). If we impose that the carrier does not have to propose at most one bundle, but he can propose all those bundles that cover the set of loads L, then the constraint (3) will be substituted by $3''$:

$$\sum_{b \in B: l \in b} x_b \leq 1 \qquad \forall l \in L \qquad (3'')$$

Using the Kronecker symbol δ_{lb} in order to express that l belongs to b or not, the covering constraint becomes:

$$\sum_{b \in B} \delta_{lb} x_b \leq 1 \qquad \forall l \in L \qquad (3'')$$

For the previous example, results that the carrier will propose 3 one-load bundles, $(4,5)$, $(2,5)$ and $(7,4)$, at the prices of 750, 378 and 372, respectively, and yielding a profit of 1433. We observe that the profit is greater than that obtained in the *Case 1).*, but this is because the sum of the prices of the 3 single-load bundles is greater than the price of the 3-load bundle. This shows that the *Case1).* perfectly explains the use of combinatorial auction and assures the correctness of the synergy concept applied in the model.

Case 3). If we consider both constraint (3) modified as

$$\sum_{b \in B} x_b \leq 2$$

and the L-covering constraint $(3'')$, then the model will propose 2 bundles consisting of loads $(2,5)$ and $(4,5),(7,4)$ at the prices of 378 and 1091, with the profit of 1401 (lower than the previous obtained for 3 single load bundles, because the price of the 2-load bundle $(4,5),(7,4)$ is lower than the sum of the individual prices of the 2 loads).

Case 4). The same results as in the (*Case 3)* can be reached by using the L-covering constraint $(3'')$ and constraint (3) modified as

$$\sum_{b \in B} syn_b x_b \leq 2$$

.

Case 5). We can also consider the L-covering constraint $(3'')$ and constraint (3) modified as

$$\sum_{b \in B} (\frac{1}{syn_b}) x_b \leq 2$$

In this case we obtain the same results as in the original situation (the model with constraint (3)), so a unique 3-load bundle proposed. If the right part of the previous modified constraint (3) is 1 or 3 there will be obtained only single bundles (1 or 3 one-load bundles, respectively).

Thus, we can observe that if we use the L-covering constraint $(3'')$ then usually will be proposed disjoint, one-load bundles (because maximizing the profit, having greater prices) and only if we restrict the right part of the modified constraint (3) (seen in the previous cases) to be lower than $|Bundle1|$ there will be obviously obtained even real (not one-load) disjoint bundles.

Since $|Bundle1|$ may be unknown (or difficult to know a priori, without solving first the original model), then maybe the constraint (3) can be removed and can be considered only the L-covering constraint $(3'')$ in the model (if we want to propose the bundles that cover all the loads of set L).

- modifying the objective function and the constraints:

In order to reach our goal to propose more than one bundle, we can modify the objective function with appropriate coefficients. We think to multiply the p_b by those coefficients involving synergy between loads (for example, the inverse of the synergy numbers of the bundles) because we want to propose more bundles (covering the set L) with higher synergy between their component loads. The O.F. becomes:

$$\max(\sum_{b \in B} syn_b p_b + R(L_0)) - \sum_{k \in K} \sum_{(i,j) \in A} \sum_{t=1}^{T-\tau_{ij}} c_{ij} y_{ij}^{kt} \qquad (1')$$

Case 6). If we consider the L-covering constraint $(3'')$ then will be chosen the same unique bundle as in the solution of the original model (even if we include or not also the constraint (3) modified).

Case 7). If consider constraint (3) then will be obtained the same results as in the original model (only the profit obviously greater, 1460).

Considering instead the constraint (3) modified

$$\sum_{b \in B} x_b \leq 2$$

then the carrier will propose the not disjoint bundles 10 and 26 consisting of $\{(4,5),(2,5)\}$ and $\{(4,5),(2,5),(7,4)\}$ at the prices of 1062 and 1467 with the profit of 2602.

Moreover, considering the constraint (3) modified as

$$\sum_{b \in B} x_b \leq 3$$

then will be obtained the same results as in *(Case 1).* with the higher (because of the synergy coefficients) profit of 3739.

And so on, modifying the right part of the constraint (3), there will be obtained more non disjoint bundles (until arriving at the number of $2^{|Bundle1|} - 1$ bundles, in our example, 7 possible bundles).

3.3 Preprocessment of the set of auctioned loads

In order to a priori overcome the dimension problem, decreasing the cardinality of the set of all possible bundles, preprocessment procedures of the auctioned loads set have been developed, taking into account both the trucks' position and the delivery time windows for the loads.

The first computational experiments, where the departure position of the trucks making up the available fleet of the carrier was established in a random way, have produced a great number of infeasible problems. Whatever the set of loads submitted in the bid is, any feasible solution has to cover at least the existing, previously booked transportation contracts for the loads. The infeasibility of the problems was mainly due to the corriers' incapacity to satisfy all the booked loads. The choice to assign the trucks' departure positions in a not completely random way comes from the necessity to reduce the infeasibility cases. Therefore the trucks' position at the beginning of the temporal horizon was assigned in the following way:

```
STEP 1. Fix the number of trucks the fleet is consisting of
        equal to the ceil of the half of the booked loads' number.
STEP 2. IF $(v_i,v_j) \in L_0$ has to be satisfied leaving
        necessarily at time $1$ such that to not overcome
        the time limits imposed by the time windows THEN
           make depart a truck from $v_i$.
        Repeat STEP 2 for every $(v_i,v_j) \in L_0$ with
        load's pickup moment equal to $1$.
STEP 3. IF the number of trucks used until this moment
        is greater than the initial number of trucks THEN
           update the number of trucks that make up the fleet.
STEP 4. IF all the trucks have not been used THEN
           assign the departing position randomly for the trucks
           still available in the fleet.
```

After having assigned the departing position for the trucks, a preprocessment of the auctioned loads becomes necessary. Indeed, between the auctioned loads generated in a random manner, could be some loads having the pickup moment the first day of the week. If the preprocessment of the loads in L will not be carried out, the carrier would consider *bundles* consisting of loads that he already knows not being able to satisfy because of the lack of trucks available (at the beginning of the temporal horizon) in the city representing the load's pick-up point. This happens since, having imposed to some trucks to transport the loads in L_0, the number of trucks available to satisfy any *load* in L with pick-up day 1, is decreased.

More precisely, this preprocessment will eliminate a load (v_k, v_l) da L if do not exist trucks available to carry it, that is if at time 1 (denoting the first day of the week) do not exist trucks leaving from v_k or they have been already assigned for satisfying the booked loads.

A detailed description of the preprocessment of the set of loads in L is provided by the following algorithm, where "difference" denotes the difference between the number of trucks leaving from v_k and the number of *loads* in L_0 with the origin in v_k, "nTrucks" denotes the number of trucks leaving from v_k and "nLoadL" denotes the number of loads in L having the origin in v_k; "matrixV" denotes the matrix keeping track of the presence or not of one or more trucks in a vertex at the initial moment.

```
  PREPROCESSMENT RESPECT TO THE DEPARTURE POSITION OF THE TRUCKS


Until all the loads in L have not been examined
  Fix $(v_k,v_l) \in L$
    IF $(v_k,v_l)$ must be satisfied leaving at time $1$
       IF $(v_k,v_l)$ has not been already processed
          IF difference$ = 0$ THEN
             //we do not have any available truck leaving from $v_k$
             update matrixV
          IF difference$ > 0$ THEN
             recall ProcLtruck // return nloadL, number of loads
             //having origin $v_k$ at time $1$, and vettL, array
             //that will contain these loads
             IF nloadL > difference THEN
                recall PreProcessment //for every load in vettL
                update mVerProc //keep track of the preprocessed loads
       IF there are no trucks leaving from $v_k$
          eliminate $(v_k,v_l)$ from $L$ //because we do not have available
```

```
                    //trucks to carry it
Repeat for a new load of L.
```

The "Preprocessment" procedure, recalled in the previous algorithm, will verify if it is possible to eliminate some of the loads in L having pick-up place in the same node, but for whom there are no any more available trucks.

This algorithm works as following: verifies the temporal compatibility (respect to the time windows) for every load in L with those in L_0; if from the comparison would results an incompatibility with all the load in L_0, then will be performed the same examination with the loads of L. If even from these comparisons will be obtained a general incompatibility, the load will be eliminate from L since it could not be satisfied.

The temporal incompatibility derives from the assumption in the model definition that every *lane* has a fixed travelling time and that every load in L_0 and in L has a time window, that is a set of days in which it could be delivered. This may lead to some loads to not fall into any route carried out by the trucks, because temporally incompatible.

Given (v_k, v_l) in L, the algorithm *preprocessment* previously described is the following:

```
                              PREPROCESSMENT

1:Recall the function preproc //return the number of incompatibilities
                              //with the loads in $L_0$
2:IF the number of incompatibilities is equal to the number of loads in $L_0$
    GO TO 1. //return the incompatibility with $L$ except for $(v_k,v_l)$
    IF the number of incompatibilities is equal to (number of load in L)$ -1$
       eliminate $(v_k,v_l)$ from $L$
```

The function *preproc* returns to *preprocessment* the number of incompatibilities between a load of L and all those of L_0 and L. It verifies the temporal compatibility with the loads in L_0, by counting the number of days common to the window associated to the load of L examined and those of the loads in L_0. If there are common days, or days in which the truck can stay in the same city before leaving it again for a load delivery or if one establishes, based on the time windows and on the delivery times, that the delivery of the load in L had to be previous to that of the load in L_0, would result that this load could not be removed from L, because could belong to some route. Conversely, if it will result to be temporaly non compatible with all the loads in L_0, it would pass to control analogously by considering the loads in L (excepted that one being examined).
In the case it will result an incompatibility of the examined load with all the loads in L_0 and in L, then would be returned tov*preprocessment* a number of intersection equal to 0, thus that load is a candidate to the elimination from L.

Let $[a_{kl}, b_{kl}]$ be the time window of the load (v_k, v_l), $[a_{ij}, b_{ij}]$ be the time window of the load (v_i, v_j).

```
PREPROC
```

```
Until all the loads in $L_0$ (or $L$) have not been examined
  1:Fix $(v_i,v_j)$ in $L_0$ (or $L$)
    IF $a_{kl}=b_{kl}=a_{ij}=b_{ij}$ THEN
       increase the number of incompatibility
    IF $a_{kl} \geq b_{ij}$ THEN
       assign $0$ to the number of common days;
       compute the second extreme of the new window;
    IF ($a_{kl}< a_{ij}$) OR ($a_{kl}<b_{ij}$) THEN
       compute the new time window;
       compute the number of common days;
    IF the number of common days $\geq 1$ THEN
       STOP. //$(v_k,v_l)$ has non empty intersection with $(v_i,v_j)$
        // in terms of their time windows
    IF the number of common days $= 0$ THEN
       IF the second extreme of the new time window $< b_{ij}$ THEN
          STOP. //the truck can stay without moving some days
       IF $a_{ij} \geq b_{kl}$ THEN
           assign $0$ to the number of common days;
         compute the second extreme of the new window;
       IF ($a_{ij}< a_{kl}$) OR ($a_{ij}< b_{kl}$) THEN
          compute the new time window;
        compute the number of common days;
       IF the number of common days $\geq 1$ THEN
          STOP. //$(v_k,v_l)$ has non empty intersection with $(v_i,v_j)$
        // in terms of their time windows
       IF the number of common days $= 0$
          IF the second extreme of the new time window $< a_{kl}$ THEN
             STOP. //the truck can stay without moving some days
       IF the first extreme of the new time window $> b_{kl}$ THEN
          increase the number of incompatibilities
  GO TO 1.
```

3.4 Synergy between loads

Optimization-based decision support tools to help carriers in their bids generation are needed in order to include the synergies between loads and to maximize the revenues derived from the bids.
In practice not all the carriers can count on a *bidding advisor* and thus they use simple methods based on past data and on their own knowledge. In the literature concerning the fleet management the synergies are very often ignored.

A model to evaluate *bundles*, given the pairwise synergy values, is proposed in [2], and algorithms for the bundle selection are developed, too.

Chang ([6]) proposes a decision support model for the carriers participating in *one-shot* combinatorial auctions. His bid advisor integrates the load information in the e-marketplace with the carriers' fleet management plans and chooses hence the desirable *bundle* of loads. The bid generation and evaluation problems are formulated as synergetic minimum cost flow problems, by estimating the average synergy values between loads through an aproximation based on the activity on the geographically next *links*.

In [24] there are identified the synergies in the available lanes, that is the economies of scope in the carrier transportation operations in order to determine the optimal packages to bid on, for maximizing the profit.

Wang e Xia ([58]) define the first-order synergies as the complementariety between a set of auctioned loads and a set of booked loads and the second-order synergies as the complementariety between a pair of sets of auctioned and booked loads. It is showed that the synergy of a *bundle* can depend on other winning bundles.

From all the studies in the literature, only in [2] it is explicitly shown how to compute the synergies between (bundles of) loads.

We want to include the synergies in the *clearing price* of a bundle, because this price is influenced by the interaction level between the auctioned loads of that bundle and the booked loads (of the existing network) of possible winner carrier, that is by the synergy between the loads.
Hence, the random variable Y_b denoting the clearing price will have a normal distribution with parameters $\mu_b = M_b \cdot syn_b, \sigma_b^2 = n \cdot syn_b^2$, that is:

$$Y_b \equiv N(M_b \cdot syn_b, n \cdot syn_b^2) \tag{3.1}$$

where M_b is the auctioneer's asked price for the *bundle* b.

It is very difficult for a carrier to know a formula for the synergy since is a "function of all environment variables". Therefore we have to determine a way to compute the synergy values between loads.

We introduce an application method of the concept of "average synergy". Let L_{00} denote the previously contracted loads of a hypotetic (phantom) carrier participating in the auction and assumed to be the possible (expected) winner.

Consider a *bundle* b consisting of n auctioned loads.
We have to evaluate the "pairwise synergy" that every load of the bundle b has with all the loads of the carrier's existing transporation network L_{00} and with the remaing loads of b. The *bundle*'s synergy will be given by the average of the all possible (made from its loads) pairwise synergy values.

The computing formula for the synergy of the *bundle* is defined by:

$$syn(b)=\frac{\sum_{j=1}^{|b|}\left(\sum_{l=1}^{|L_{00}|} pairwisesyn(j,l)+\sum_{k<j} pairwisesyn(j,k)\right)}{|b||L_{00}|+\binom{|b|}{2}}$$

In the sequel, the algorithm for determining the synergy of a bundle of loads:

BUNDLE SYNERGY

for all $(v_i, v_j) \in b$ **do**
  for all $(v_r, v_s) \in L_{00}$ **do**
    $pairwisesynergy\,((v_i, v_j), (v_r, v_s), Syn)$
  end for
  for all $(v_r, v_s) \in b \setminus (v_i, v_j)$ **do**
    $pairwisesynergy\,((v_i, v_j), (v_r, v_s), SynLL)$
  end for
end for
$syn(b) = average \quad pairwise \quad synergy$

3.4.1 Distance-based synergy algorithm

A first approach to quantify the synergy between two loads is based on the analysis of the distance between them.
The distance between two nodes is considered, for simplicity, equal to the travelling time associated to the arc connecting them.

We consider now an auctioned load and a booked load.
At first, we have to verify if there is time compatibility between the two loads (as described in the algorithm below). If the loads result incompatible means that between them does not exist complementarity, so the synergy value is set to 1. Two arcs (representing loads)$(v_i, v_j), (v_r, v_s)$ are said to be incompatible if the arc (v_i, v_j) can not be run before the arc (v_r, v_s). If the loads result instead compatible they will have synergy more or less strong depending on the number of days of "intersection" and of the distance between them.

The algorithm that compute the pairwise synergy for two loads based on their distance is:

dist pairwise synergy$((v_i, v_j), (v_r, v_s), synergymatrix)$
if $(a_{ij} = a_{rs} = b_{ij} = b_{rs})$ **then**
  $sin1 \leftarrow 1$
  $sin2 \leftarrow 1$
end if
else (*)

if $(a_{ij} \geq b_{rs})$ **then**
  $sin1 \leftarrow 1$
end if
else
if $(a_{ij} < a_{rs} \quad or \quad a_{ij} < b_{rs})$ **then**
  $G = [a_{ij} + dist(j,r) + tau(r,s), b_{ij} + dist(j,r) + tau(r,s)] \cap [a_{rs}, b_{rs}]$
  if $(G = 0 \quad and \quad a_{ij} + dist(j,r) + tau(r,s) > b_{rs})$ **then**
    $sin1 \leftarrow 1$
  end if
  else
  $sin1 \leftarrow TabSyn[G][dist(j,r)]$
end if
$repeat \quad from \quad (*) \quad for \quad sin2$
return $pairwisesyn \leftarrow \frac{sin1+sin2}{2}$

We note that the pairwise synergy for $(v_i, v_j), (v_r, v_s)$ is different from that of $(v_r, v_s), (v_i, v_j)$; for this reason it is chosen to make an average of the obtained values such that to assign to the pair of loads a (symmetric) synergy value.

The best case is when the two loads have the biggest number of days in common and zero distance (maximum synergy), while the worst case, besides the time incompatibility situation, is when the loads have the smallest number of common days and great distance between them.

3.4.2 Hop-based synergy algorithm

A second approach to quantify the synergy between two loads is based on the number of *hop*. It is called *hop* a lane that a vehicle has to run on empty in order to reach another city.
Given two nodes, one of the following situations is possible:

- doesn not exist the direct arc connecting them => $numhop = 0$;
- exists the direct arc connecting them => $numhop = 1$;

- the shortest path it is obtained by passing by an intermediate node => $numhop = 2$;

Since on a *hop* a carrier travels empty, unloaded, he will support only a travelling cost, without any revenue. Therefore, lower the number of empty lanes in the *routing* of a vehicle, smaller the cost supported by the carrier. From here the idea to analyze the type of lanes connecting two cities.
Assume, for example, that there exists the direct arc between two nodes, that is the number of *hop* associated to this pair of nodes is 1. If this lane is corresponding to an auctioned or to a booked load, it will provide a revenue to the carrier, and the lane will not be considered a *hop*; hence the number of *hop* will decrease to 0.

The algorithm that compute the pairwise synergies based on the number of *hop* is reported below.
Consider as in he previous section an auctioned load and a booked load and verify their time compatibility.
If the loads result incompatible means that between them does not exist complementarity, so the synergy value is set to 1. Otherwise, the transportation of the first load is prior to that of the second load, the type of lanes connecting them is studied. If there are corresponding to auctioned or booked loads, then it is compared even the time windows, in order to decide that the number of hop can be decreased. So between the two loads it is a stronger synergy that seems to be or is expected.

hop pairwise synergy$((v_i, v_j), (v_r, v_s), synergymatrix)$
if $(a_{ij} = a_{rs} = b_{ij} = b_{rs})$ **then**
  $sin1 \leftarrow 1$
  $sin2 \leftarrow 1$
end if
else (*)
if $(a_{ij} \geq b_{rs})$ **then**
  $sin1 \leftarrow 1$
end if

```
else
if (a_ij < a_rs  or  a_ij < b_rs) then
  G = [a_ij + dist(j,r) + tau(r,s), b_ij + dist(j,r) + tau(r,s)] ∩ [a_rs, b_rs]
  if (G = 0  and  a_ij + dist(j,r) + tau(r,s) > b_rs) then
    sin1 ← 1
  end if
  else
  if (numhop ≠ 0) then
    if (IntermediateNodes[v_j][v_r] = 0) then
      if (search((v_j, v_r), L_00) = NO) then
        search((v_j, v_r), L)
      end if
    end if
    else
    if (IntermediateNodes[v_j][v_r] = v_k) then
      if (search((v_j, v_k), L_00) = NO) then
        search((v_j, v_k), L)
      end if
      if (search((v_k, v_r), L_00) = NO) then
        search((v_k, v_r), L)
      end if
    end if
  end if
  sin1 ← TabSyn[G][numhop]
end if
repeat  from  (*)  for  sin2
return  pairwisesyn ← (sin1+sin2)/2
  ......................................
procedure search((v_j, v_r), set)
for all ((v_m, v_n) ∈ set) do
  if (m = j  and  n = r) then
    da ← a_ij + dist(j,r)
    db ← b_ij + dist(j,r)
    if (da ≥ a_mn  and  db ≤ b_mn) then
      numhop ← numhop − 1
    end if
  end if
```

end for

The algorithm computing the pairwise synergy value for loads based on the concept of distance between two cities (destination of one and origin of another) gives importance to the time employed to transport a load and not to the type of the carried load, hence to the possible revenue derived from it. The hop based algorithm, instead, gives importance to the type of the transported load, hence booked, auctioned or empty repositioning lane, despite of the time need to carry it, so the cost derived from it.

3.5 Chance constraints expression according to the normal distribution

With the aim to explain the uncertainty related to the results of the auction, the lowest bid price between all the carriers competing for each load, called the *clearing price*, is modeled as a random continuous variable, assumed normally disributed.

A random normal (or gaussian) variable X is a continuous random variable usually denoted by $X \equiv N(\mu, \sigma^2)$. The two parameters, called *expected values*, that is μ and σ^2, corresponds to the mean $E(X)$ and variance $Var(X)$ of the distribution. Indead, it can be proved that $E(X) = \mu$ e $Var(X) = \sigma^2$. Hence, every normal distribution is uniquely defined by the mean and the variance.
The random gaussian variable is characterized by the probability density function, often referred as *gaussian function*:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad , x \in \Re \tag{3.2}$$

described by symmetric and bell curve (*Gauss curve*.
The particular case where the mean ($\mu = 0$) and the variance ($\sigma^2 = 1$) is known as **standard normal variable** and is indicated by $N(0, 1)$.

The cumulative distribution function Φ of the standard normal distribution is

$$\Phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{u^2}{2}\right)} du \tag{3.3}$$

and the quantile function Φ^{-1} can not be expressed in a close form in terms of elementary functions. Therefore, approximated values of this functions are available only in tables and can be obtained by using approximating calcol algorithms.
Consider a bundle b consisting of n auctioned loads. Assume that, for every load i of the *bundle*, the random variable representing the lowest bid of the carriers competing for that load is denoted by X_i $(i = 1, ..., n)$ and have a normal distribution given by:

$$X_i \equiv N(\mu_i, \sigma_i^2) \tag{3.4}$$

where the mean value μ_i is assumed equal to the auctioneer's asked price M_i for the auctioned load i and the estimation of the standard deviation σ_i of the probability density function describing the load price is assumed equal to 1.
In practice, the variables are dipendent because the bid price for a load depends on the prices of the near loads, but the modeling and the simulation of multivariate dependent random variable is always a complex problem in the applications. Therefore, it has been assumed that the normal random variable X_i are independent.

We consider thus the random variable Y_b, the clearing price of the *bundle* b as following:

$$Y_b = \sum_{i=1}^{n} X_i \tag{3.5}$$

The following theorem holds, expressing the important property of invariance respect to the sum of the independent variables.

Theorem *Linear combinations of normal and independent random variables are normally distributed, too.*

Hence, it follows that:

$$Y_b \equiv N(\mu_b, \sigma_b^2) \tag{3.6}$$

where

$$\mu_b = \sum_{i=1}^{n} \mu_i \qquad \sigma_b^2 = \sum_{i=1}^{n} \sigma_i^2 \tag{3.7}$$

Since we have assumed $\mu_i = M_i$ $(i = 1, ..., n)$, we obtain $\mu_b = \sum_{i=1}^{n} \mu_i = \sum_{i=1}^{n} M_i = M_b$, (that is equal to the ask price for the whole bundle b) and $\sigma_b^2 = n$. It follows that:

$$Y_b \equiv N(M_b, n) \tag{3.8}$$

The chance constraints of the model proposed for the BGP in Chapter 3, expressed according to the normal distribution of the *clearing price* of each *bundle*, are the following:

$$p_b x_b \leq \mu_b + \sigma_b \Phi^{-1}(\alpha) \quad \forall b \in B \tag{3.9}$$

where Φ^{-1} is the inverse function of the cumulative distribution function for a standard normal distribution.

This inverse can be determined from the tables existing for the the cumulative distribution function. For example, for $\alpha = 0.05$ we have that $\Phi^{-1}(0.05) \approx -1.65$.

From the probabilistic type constraint we have that the confidence level is equal to $1 - \alpha$, with $\alpha \in [0, 1]$. It expresses the degree of certainty of the result. For example, if α is 0.05, then "In 95% of the cases the bid price for a bundle is lower than the *clearing price* of that bundle or there is a 95% chance that the submitted bundle will win the auction".

Chapter 4

The proposed heuristic approach

In this chapter are described the heuristic methods proposed for the solution of the BGP model. There are presented two categories of sequential heuristics: the first category heuristic generate a bundle of loads, starting from the maximal/minimal cardinality bundle and evaluating the decremental/incremental marginal benefit of dropping out/inserting a load and updating the current bundle; the second category heuristic selects from a set of bundles generated respect to different criteria, the best one, that is the bundle with the highest value of the objective function.

4.1 Introduction

Since the number of the constraints and variables related to the bundles of auctioned loads is exponential, the model proposed in chapter 3 for the BGP was solved exactly (using Branch and Bound) only up to a certain dimension, more precisely, up to 20 auctioned loads.

For higher dimensions have been build some heuristics that permit a sequential resolution of the problem.

In the literature there are proposed for the BGP solution methods that consider the Lagrangian relaxation and column generation or some kind of decomposition methods.

In [24], the nonlinear (quadratic) integer model is solved by using a decomposition approach based on column generation and Lagrangian relaxation, thus a decomposition based heuristic is developed. The decomposition strategy involves a partition of the model into a master problem and a subproblem for which a column generation-like strategy is employed to derive approximate solutions to the original carrier formulation.

In [58], two heuristic methods are proposed for generating combinatorial bids.

The first heuristic, based on a fleet assignment model, give a generic formulation for the routing and scheduling problem and solve it; group the lanes assigned to the same vehicle into one combination then the resulting bid consists of all the combinations.

The second heuristic, based on the nearest insertion method, have as the basic idea to insert a lane into an assignment for any vehicle that minimizes the total empty travel distance and do this to all lanes, one by one, until they are all assigned. It is realized the construction of heuristic assignment and the generation of combinatorial bids is done like in the first heuristic. Heuristic 1 is computationally complicated, whereas Heuristic 2 is easy to implement.

Numerical experiments for comparing the performances of the two heuristics show that, on average, the simple nearest insertion heuristic underperforms the integer programming-based optimal fleet assignment model in most instances, but it may outperform the latter by up to 8% in some instances and by 5% (in terms of the total expected empty distance travelled) in many other instances.

In [53], the Bid Construction Problem (BCP) in combinatorial auctions for the procurement for freight transportation contracts is studied in two different scenarios: in the absence of pre-existing commitments and in the presence of pre-existing commitments. Computationally efficient optimization-based approximation algorithms for solving the above problem in each scenario are also proposed.

The main idea of the proposed strategy to generate bids is that the carrier construct bids such that the total operating empty movement cost is minimized. Since this requires solving a TL VRP, the authors follow an approach similar to that one of solving VRP: set partitioning (SP) formulation of the problem and column generation method for exact solutions. The first step of the bidding strategy consists in using a search algorithm (depth first search algorithm) to enumerate all routes with respect to routing constraints and treat each route (candidate bid) as a decision variable in the SP formulation of the BCP (BCP-SP). The new lanes in this route form the set of items bid, its reservation cost determines the bid price and can be calculated, as in [52], on the base of route length, empty movement cost and carriers' profit margin. In BCP-SP is imposed the constraint that each lane is covered only by one optimal bid (two optimal bids are mutually exclusive of new lanes). In order to explore all the bidding opportunities for substitutable bids, the above set of constraints is relaxed in the BCP-SP formulation, remodelling it as a Set Covering problem (BCP-SC). To solve it the authors propose the use of a modified Branch and Bound algorithm that search until all optimal solutions are found. Moreover, for substitutable bids, is used the Bid Set Augmentation Rule in order to detect additional bidding opportunities.

For the second scenario, the previous bid construction strategy is extended to the situation in which carriers already have commitments to other contracts prior to the auction (carriers may have contracts serving multiple customers). Carriers will not only deliberate on their bidding plans (on the base of combinational opportunities among new lanes) but also will have integrate these new lanes into their current operations. Moreover, XOR bids are developed for any two atomic bids that have substitutable valuations with respect to a common set of current lanes.

Finally, the bids that conflict with pre-existing routing plans are identified and excluded by using the Bid Substitution Condition.

The performance of the proposed bid construction method respect to complete enumeration was studied by using a simulation-based experiment. The number of atomic bids generated by the above method (for the two scenarios) is significantly fewer than that of complete enumeration and thus, it is much faster than the complete enumeration method in terms of computation time. The quality of the bids constructed by the new method is quite close to that of the complete enumeration method; the performance of the proposed method in terms of number of new lanes won by each of the carriers ("Smart" or Enumeration) and the empty movement costs after auction is quite good.

The optimization-based bid construction strategy presented in [53] results optimal for carriers in terms of operational efficiency in the absence of pre-existing commitments and near optimal when pre-existing commitments are also considered. Moreover, the benefit of the approximation method proposed is that it provides a way for carriers to discover their true costs and construct optimal or near optimal bids by solving a single NP-hard problem, so a significant improvement in computational efficiency.

As already said, our model for the BGP proposed in Chapter 3 determines not only the best bid to submit and its price, but even assigns the loads to the carrier's trucks, providing the corresponding routing.

The problem of assigning jobs to vehicles in a transportation network is wellknown in the area of vehicle routing problems (VRP) as a real-time multivehicle pickup and delivery problem with time-windows. Such problems arise in the transportation of elderly and/or disabled persons, shared taxi services, certain courier services and so on.

The VRP and its variants have been studied extensively (see [20] and [55] for a survey. It is well-known that most variants of the VRP problem are NP-hard, so that it is virtually impossible to find an optimal solution within a short time. Most work focuses on static and deterministic problems where all information is known when the schedule has to be generated (see, for example, [8]. The dynamic assignment problem, as discussed in [15], also shows some similarities. Here resources (e.g. vehicles) are dynamically assigned to tasks that arrive during schedule execution. Key differences are:

(1) each individual vehicle schedule contains only one job at a time;

(2) the price of a job is exogenous and the only issue is whether to accept this job and if so, to assign a vehicle to this job;

(3) only the most profitable jobs are accepted.

Powell and Carvalho ([36]) use so-called Logistics Queuing Networks (LQN) to decompose the large and complex scheduling problem by a series of very small problems. In this way, many real world details can be included in the model that cannot be dealt with using traditional approaches. Still this is a centralized planning approach.

Closely related work can also be found in ([39]; [40]; [41]) who investigate the dynamic assignment of vehicles to loads for real-time truckload pickup and delivery problems. They provide relatively simple and fast local rules. Yang et al. ([59]) extend this work to a formal optimization-based approach for the same problem class. They use simulation to compare this approach with the previously developed heuristics. Mahmassani et al. ([27]) present a hybrid approach combining fast heuristics for initial assignment with the optimization-based approach for the off-line problem of reassigning and sequencing accepted loads. Several approaches for routing and scheduling in oversaturated demand situations are developed in [28].

4.2 Sequential heuristics of type I

A first category of heuristic method starts from the bundle of loads of maximal cardinality (that is, equal to the set of the auctioned loads

L). Evaluate the decremental profit (marginal benefit) for each bundle obtained by dropping out (deleting) one load at a time from the current bundle, and choose the load for whom it has been yield the best decremental profit. Then update the current bundle (eliminating the previously selected load) and so on. The procedure is repeted until the current bundle becomes empty. Let $f(S)$ be the objective function value obtained by solving the BGP when the auctioned loads set is given by $S \subseteq L$.

The heuristic algorithm previously described is the following:

SEQUENTIAL DESCENDING HEURISTIC ALGORITHM OF TYPE I

Pick initial subset $S^0 = L$

1 : FORALL $i \in S^0$

compute the marginal benefit of dropping load i from the

current set as $\rho(i) = f(S^0 \setminus \{i\}) - f(S^0)$

Determine $i^\star = argmax \quad \rho(i)$

Update S^0 as $S^0 = S^0 \setminus \{i^\star\}$

IF S^0 is not empty THEN GO TO 1, ELSE STOP.

A version of this heuristic can be obtained by considering as the initial bundle that one with minimal cardinality (for example, the empty set) and evaluating the incremental profit (at adding a load to the current bundle).

The heuristic algorithm previously described is the following:

SEQUENTIAL ASCENDING HEURISTIC ALGORITHM OF TYPE I

Pick initial subset $S^0 = \emptyset$

1 : FORALL $i \in L \setminus S^0$

compute the marginal benefit of adding load i to the

current set as $\rho(i) = f(S^0 \cup \{i\}) - f(S^0)$

Determine $i^\star = argmax\rho(i)$

IF $\rho(i^\star) > 0$ THEN

```
update S^0 as S^0 = S^0 ∪ {i*}
IF S^0 = L THEN STOP, ELSE GO TO 1.
```

The complexity of this first type of heuristics will be only of $\mathcal{O}(n^2)$ (where n is the cardinality of the set of the auctioned loads).

4.3 Sequential heuristics of type II

A second category of heuristics considers as the initial set of bundles a certain set of bundles selected with respect to various criteria (random selection, bundles chosen with higher synergy and/or in some interval, bundles with cardinality in some interval, etc...). Then solves the problem for each bundle of this set and select from these the bundle with maximum value of the objective function.

Let $\bar{B}$ be the initial set of bundles, instead of the set B of all possible bundles formed with the loads of L. The set $\bar{B}$ is determined by using the above mentioned criteria.

The heuristic algorithm previously described is the following:

```
SEQUENTIAL HEURISTIC ALGORITHM OF TYPE II

FORALL b ∈ B̄
solve the BGP with B = {b};
Let z_b be the optimal (objective function) value
Solve the problem max_{b∈B̄} z_b, let b* be the optimal solution.
The (near) "‘optimal"’ bundle, heuristic solution of the BGP
(with B = B̄) is given by b*.
```

Chapter 5

Computational results

Several computational experiments have been carried out in order to validate the proposed BGP model and to measure the efficiency and the efficacy of the previously considered heuristic solution strategies. Since for the combinatorial auctions, in general, there are not publicly available real data (as is often signaled in the leterature, for example in [2]), a test problems' generator has been constructed and implemented in C language and compiled by using Dev-C++ (versione 4.9.9.0).

5.1 Test problems configuration

In order to simulate combinatorial auctions data, an automated problems generator has been produced; thus, a significant set of test instances has been obtained.

We create the complete graph $G = (V, A)$ (introduced in Chapter 3) with the nodes representing the cities and the arcs all the possible direct links (streets) between cities.

The travelling times matrix τ, the distance matrix $Dist$ and the costs matrix $Cost$ have been generated as follows:

- The matrix τ has been randomly generated according to an uniform distribution in the range $[1, 3]$; we have assumed that the travel time from a node to itself , that is the time to stay in a node, is equal to 1 day ($\tau_{ii} = 1$ for every i) and that the matrix τ is symmetric ($\tau_{ij} = \tau_{ji}$ for every i and j).

- The matrix $Dist$ has the elements given by:

$$dist_{ij} = \tau_{ij} \cdot 90 \cdot 8$$

  because we have assumed that a truck travels at the average speed $90km/h$ and that the number of working hours of the trucks' drivers is fixed to $8h/day$.
  For the sake of simplicity, we have assumed that $dist_{ij} = \tau_{ij}$ for every $i \neq j$ and $dist_{ii} = 0$.

- The cost matrix $Cost$ has the elements direct proportional to the distance, defined by the following formula:

$$costo_{ij} = (270 + random(0, 50)) \cdot dist_{ij}$$

where 270 Euros represents the minimum cost of traveling on the lane and $random(0, 50)$ is a random number, having uniform distribution between 0 and 50, that represents possible cost variations due to the increase of the fuel price, of the highway taxes, etc...
The minimum cost of 270 Euros has been obtained by assuming that:

- a truck runs at an average speed of $90km/h$;
- a truck travels $5km/l$;
- the fuel costs $1,4$ $Euro/l$
- the working day is about $8h$;
- a driver gains 68 Euros daily.

Successively, assuming that the initial graph was not constructed on the shortest path, that is, it did not have the minimum distance arcs between nodes, a reduced graph has been generated by using the Floyd Warshall's algorithm. Therefore, the new set of arcs will be $A' \subset V \times V$; the sets L_0 of booked loads and L of auctioned loads will be generated by selecting randomly two subsets of A'.
We have assumed that the number of loads in L is equal to the number of loads in L_0.
A time window was associated to every booked load and to every auctioned load. In both cases, the time window extremes represent the first and the last possible day of delivery of the load.
The first extreme of the time windows associated to a load l in $L0$ was generated according to the following formula:

$$a(l) = \tau_{ij} + uniform(1, T - \tau_{ij})$$

The second extreme $b(l)$ is obtained from the same formula, by imposing only that it is has to be greater than or equal to $a(l)$. The temporal horizon T has the length of 7 days, hence we can have time windows with the minimal length of 1 day and the maximal length of 6 days. The choice of associating time windows completely random to the loads in $L0$ derives from the fact that the existing transportation network is the result of more auctions previously won by the carrier, organized by the shippers having different needs in terms of delivery times.
For the auctioned loads instead, three different types of time windows have been simulated:

(1). *short*: with at most two delivery days;

(2). *medium*: with at most three delivery days;

(3). *long*: with at most four delivery days.

The time τ_{ij} of travelling on a lane influences the delivery time of a load. Therefore, the first "possible" delivery day will have to be at least equal to

the travel time associated to the load plus an additional time, expressed in number of days, randomly chosen according to a uniform distribution in a range between 1 (first day of the week) and the day obtained by the difference between the temporal horizon length, the travelling time and a random number (depending on the window type). Hence $a(l)$ can be at least 2, as in the L_0 case. The $b(l)$ will be computed starting from the first extreme and adding a random number, based on the time windows type.
Thus, the time windows will be obtained as follows:

- the first delivery time will be given by the following formulas:
  - $a(l) = \tau_{ij} + uniform(1, T - \tau_{ij} - uniform(0, 1))$ (short)
  - $a(l) = \tau_{ij} + uniform(1, T - \tau_{ij} - uniform(0, 2))$ (medium)
  - $a(l) = \tau_{ij} + uniform(1, T - \tau_{ij} - uniform(0, 3))$ (long)
- the last delivery time will be given by the following formulas:
  - $b(l) = a(l) + uniform(0, 1)$ (short)
  - $b(l) = a(l) + uniform(0, 2)$ (medium)
  - $b(l) = a(l) + uniform(0, 3)$ (long)

The number of trucks and their position at the beginning of the temporal horizon have been generated as described in the Chapter 3. First, it is taken a number of trucks equal to the ceil of the half of the number of loads in L_0. Next, if the number of booked loads with the pickup day 1 exceeds the number of available trucks, the latter will be updated.
The departing position of the trucks has been assigned as follows:

(1). if there are one or more booked loads leaving from the node v_i at time 1, it is imposed that from v_i are leaving as many trucks as those loads;

(2). the departing position is randomly assigned to the remaining vehicles not yet assigned to nodes at (1).

Therefore, a preprocessment of the auctioned loads will be made based on the trucks' departing positions and the three types of time windows associated to loads in L. A load will be eliminated from L if it has to be picked up in the first day of the week and there are no available vehicles in that node to transport it. At the end of this preprocessment there will be obtained three different set of auctioned loads, corresponding to each type of time windows.

For every set L' yield from the preprocessment, it will be computed the power set (without the empty set), so all the $2^n - 1$ possible *bundles* of auctioned loads, where n is the cardinality of L'.

The revenue derived from the booked loads (contracted in previous auctions) is computed by adding the 40% to the sum of the costs of those loads.

Based on the distances between cities and the range of delivery days for the loads, a first table (**5**.1) with synergy values to associate to pair of arcs can be produced.

Ten synergy levels are defined: if the loads are temporaly incompatible the pair of loads has the synergy of 1. If there is temporal compatibility the levels of synergy go from the inferior one (0.95) corresponding to a scarce interaction between loads to the superior one (0.50) representing the maximum possible interaction (complementarity) between two loads.

Based on the range of delivery days for loads and the number of hop between two cities a second table (**5**.2) with synergy to associate to every pair of arcs is constructed.

The parameters of the proposed stochastic model for *bidding advisor* are:

- the cardinality of the set of the cities and the cardinality of the

		distanza			
		0	1	2	3
	0	0.6	0.8	0.95	0.95
(time windows)	1	0.55	0.75	0.90	0.90
intersection	2	0.55	0.75	0.90	0.90
days	3	0.5	0.7	0.85	0.85
	4	0.5	0.7	0.85	0.85
	5	0.5	0.7	0.85	0.85

Table **5**.1: Distance-based pairwise synergies

		hop		
		0	1	2
	0	0.6	0.8	0.95
(time windows)	1	0.55	0.75	0.90
intersection	2	0.55	0.75	0.90
days	3	0.5	0.7	0.85
	4	0.5	0.7	0.85
	5	0.5	0.7	0.85

Table **5**.2: Hop-based pairwise synergies

auctioned loads' set;

- the synergy between loads (no synergy, distance-based synergy, hop-based synergy);
- value of α in the confidence level definition.

In the tests of the next section there will be examined the effects of every parameter's changing while the other parameters will be fixed.

All the described data will be generated and saved in distinct files or one file and imported in the model's implementation in GAMS or

Microsoft C++, and will constitute an instance for the BGP (solved by using the MIP solver ILOG CPLEX).

5.2 Numerical results

5.2.1 Exact solution

The first experiments made by using the implemented model (in GAMS), have produced solution to problems with 10 cities and 12 auctioned loads. For higher dimension instances, there will be an exponential computational complexity and the system will yield out of memory.
In order to pass this limitation, first it has been done an iterative solving of the model, by considering partitions of the set of possible *bundles*. At every iteration the problem is solved for each partition, the objective function values obtained and the corresponding chosen *bundle* are saved. At the end of the last iteration it is selected between the various chosen packages that one corresponding to the maximum value of the objective function. That *bundle* is the best bid , that is maximizing the carrier's profit, that he can submit in the auction.

By these experiments it is verified until what instance dimension the BGP can be exactly solved. Because of the exponential number of variables and constraints (corresponding to the bundles of auctioned loads), the proposed model can be solved exactly in reasonable execution times only up to less than 20 auctioned loads. For 20 auctioned loads the solution time is most of the time exceeding the 5 days.

In the first experiment the number of cities (nodes) and of the auctioned loads (arcs) is varied. The model is tested on 8, 14 and 18 nodes and on 8, 13 and 16 arcs, since in the optimal solution's searching on instances with 20 auctioned loads the computational time limit (fixed to 5 days) is exceeded.

For each nodes-arcs combination five instances were executed (so a total of 45 tests). In the table (**5**.3) the cardinality of the chosen bundle is reported for each test.

	8 arcs		13 arcs		16 arcs	
	Test	$\|b\|$	Test	$\|b\|$	Test	$\|b\|$
8 nodes	$T1$	5	$T1$	7	$T1$	6
	$T2$	4	$T2$	6	$T2$	5
	$T3$	4	$T3$	5	$T3$	5
	$T4$	4	$T4$	6	$T4$	8
	$T5$	3	$T5$	6	$T5$	9
14 nodes	$T1$	3	$T1$	4	$T1$	4
	$T2$	3	$T2$	6	$T2$	6
	$T3$	3	$T3$	7	$T3$	6
	$T4$	4	$T4$	8	$T4$	4
	$T5$	3	$T5$	6	$T5$	5
18 nodes	$T1$	3	$T1$	6	$T1$	6
	$T2$	3	$T2$	4	$T2$	7
	$T3$	3	$T3$	4	$T3$	6
	$T5$	4	$T5$	5	$T5$	6
	$T5$	3	$T5$	6	$T5$	5

Table **5**.3: Cardinality of the chosen *bundle*

We can observe that, by increasing the number of auctioned loads, the cardinality of the chosen bundle is almost always increased. But the number of the network nodes has no influence on this cardinality.

This is more evident in the table (**5**.4) where the average number of loads of the chosen *bundle* is reported for each nodes-arcs combination.

The computational times employed by GAMS to solve the problem is

	8 arcs	*13 arcs*	*16 arcs*
8 nodes	4	6	6.6
14 nodes	3.2	6.2	5
18 nodes	3.2	5	6

Table **5**.4: Average cardinality of the chosen *bundle*

increasing with the cardinality of the auctioned loads set L. For 8 auctioned loads it takes few minutes to solve the problem, but the execution times arise to about 4 hours for solving the instances with 13 auctioned loads and to an average of 7 hours for those with 16 loads.

In the next experiment is studied how the synergy value between loads influences the price of the chosen bundle, hence the carrier's fleet management plan. Nine different problem instances for the 14 nodes-8 arcs combination are run. The confidence level is of 95%.

In the table (**5**.5) $|b|$ denotes the cardinality of the chosen *bundle*, M_b denotes the price the shipper is willing to pay for this bundle (*ask price*), P_b denotes the prices assigned to the *bundle* (in Euros) for the synergy levels distance-based $synd_b$ and hop-based $synh_b$. SS, SD and SH represents the scenario with no synergy between loads, the scenario with the distance-based computed synergy and hop-based synergy, respectively.

By analysing the results reported in the table (**5**.5) we remark that the synergy value associated to the bundle by using the hop-based algorithm is lower than or equal to the synergy value associated to it by the distance-based algorithm. In the absence of synergy (scenario SS), the bundle synergy value is 1 and it is omitted from the table.

From the table we can observe that the more frequent (50% of all the results) synergy value for a bundle is 0.85. Then the value of 0.90 appears in 39% of the tests and 0.80, the maximum synergy level here, is associated to bundles only in 11% of the cases.

It is obtained that, by varying the synergy values, the model proposes

	SS			SD			SH		
	$\|b\|$	M_b	P_b	$\|b\|$	$synd_b$	P_b	$\|b\|$	$synh_b$	P_b
test 1	2	922	919	2	0.90	827	2	0.85	781
test 2	3	1899	1896	3	0.90	1707	3	0.85	1612
test 3	3	1434	1431	3	0.90	1288	3	0.85	1216
test 4	3	1442	1439	3	0.90	1295	3	0.85	1223
test 5	3	1885	1882	3	0.85	1600	3	0.80	1506
test 6	3	1834	1831	2	0.85	781	2	0.85	781
test 7	3	2274	2271	3	0.90	2044	3	0.85	930
test 8	4	2722	2718	4	0.90	2446	3	0.90	2042
test 9	3	1402	1399	3	0.85	1189	3	0.80	1119

Table **5**.5: Bundle price determination by varying the synergies

the same bundle in 7 tests from all 9. In test 6 the model proposes in the SS scenario a bundle of 3 loads while in the other scenarios a different bundle of minor cardinality, because in this way the carrier's profit is maximized (as it is the objective of the BGP). An analogue situation is verified in test 8 where, for the SH scenario it is chosen a bundle of minor cardinality respect to that one chosen in the other scenarios, but is the bundle that maximize the expected carrier's profit. Moreover, one can observe that the price of the bundle in the scenario SH is lower than that one in the scenario SD, except the test 6 where it is assigned the same price. We can see how the synergies influence the price of the bundle of auctioned loads, decreasing the bid price. A lower bid price means a decreasing of the carrier's profit but the bid will be more competitive respect to the bids submitted by the others carriers participants in the auction. The winning probability of the load influences the choice of the bundles to bid on. We assume the parameter α used to compute the confidence level has the following values $0.05, 0.10, 0.15, 0.20, 0.25$).

The experiment considers the 14 nodes-8 arcs combination and the bundle synergy computed based on distance.

	$\|b\|$	$synd_b$	0.05	0.10	0.15	0.20	0.25
test 1	3	0.95	1388.09	1388.69	1389.10	1389.42	1389.69
test 2	3	0.90	1718.24	1718.80	1719.19	1719.49	1719.75
test 3	3	0.85	1599.66	1600.19	1600.56	1600.84	1601.09
test 4	3	0.90	1294.88	1295.44	1295.83	1296.13	1296.39
test 5	3	0.90	1287.68	1288.24	1288.63	1288.93	1289.19
test 6	3	0.90	1706.72	1707.28	1707.67	1707.97	1708.23
test 7	3	0.95	2661.85	2662.45	2662.86	2663.18	2663.45
test 8	4	0.90	2446.48	2447.13	2447.58	2447.93	2448.23
test 9	3	0.85	1188.94	1189.48	1189.84	1190.12	1190.37

Table **5**.6: Bundle price by varying α

In the table (**5**.6) it can be observed that by increasing the value of the parameter α the price of the chosen bundle is increased too (obvious behaviour according to the chance constraints).

Therefore, the increasing of the bundle price obviously determines an increasing of the objective function value, that is of the expected carrier's profit. The objective function values are reported in the table (**5**.7). By analysing the results of this experiments we can say that, if the carrier chooses $\alpha = 0.05$, he will have 95% chance of winning the bundle submitted as bid, whose price is very low. Otherwise, if the carrier chooses the α value close to 0.25, he will have only 75% probability of winning the package but if he wins it, he will obtain the bundle at a higher price and so he will have a major profit.
An analogue behaviour can be expected in the case of the hop-based synergy.

α	0.05	0.10	0.15	0.20	0.25
test 1	523.49	524.09	524.50	524.82	525.09
test 2	738.24	738.80	739.19	739.49	739.75
test 3	228.06	228.60	228.96	229.24	229.49
test 4	716.08	716.64	717.02	717.33	717.59
test 5	701.28	701.84	702.23	702.53	702.79
test 6	153.52	154.08	154.47	154.77	155.03
test 7	549.25	549.85	550.26	550.58	550.85
test 8	712.08	712.73	713.18	713.53	713.83
test 9	168.34	168.87	169.24	169.52	162.77

Table **5**.7: Carrier's revenue by varying α

5.2.2 Heuristic solution

For higher dimensions heuristic procedures that permit a sequential solving of the BGP have been constructed. Extensive computational tests are carried out on a meaningful number of test problems, with the goal of assessing the behaviour of the proposed approaches. Thus, the various proposed heuristics have been compared, providing the corresponding computational times and the gap with the best (optimal) solution (up to the dimension the BGP has been exactly solved).

The sequential solving (in GAMS) described in Chapter 3 leads to important improvement in terms of execution times. Indead, in the table (**5**.8) are reported the results obtained for 8 instances where the number of auctioned loads was fixed to 10. In the first column is quoted the number of nodes, in the second one the name of the test, in the third and fourth column the time employed by the CPU to find a solution: in the first case, the model has been solved by considering all the possible bids simultaneously, in the second case instead the model has been iteratively solved. The last column contains the reduction of the execution time obtained by solving the model in an iterative way.

Number of nodes	**INSTANCE**	**CPU C (s)**	**CPU I (s)**	**REDUCTION**
10	P1	1753	214	88%
10	P2	1467	272	82%
10	P3	601	177	71%
15	P4	85	42	51%
15	P5	61	44	28%
15	P6	93	55	41%
20	P7	933	247	74%
20	P8	1403	267	81%

Table **5**.8: Computational times comparison

In the table (**5**.9) the average computational times are reported for each nodes-arcs combination.

Number of nodes	**CPU C (s)**	**CPU I (s)**	**REDUCTION**
10	1273.67	221.0	80.33%
15	79.67	47.0	40.0%
20	1168.0	257.0	77.5%

Table **5**.9: Average computational times

Respect to the GAMS implementation, the Microsoft C++ implementation runs even more faster. We repeat the same tests as before (for the same combinations of nodes-arcs) by running the implementation in MS C++ of the proposed model for BGP, with or without the use of the heuristic procedures. CPLEX 10.1.0 is used for solving the underlying mixed integer problems.

The sequential solving heuristic algorithms described in Chapter 4 leads to important improvement in terms of execution times. Indead, in the tables (**5**.10) and (**5**.11) the average computational times for each nodes-arcs combination are reported in the cases the sequential ascending heuristic and descending heuristic, respectively, of type I is used.

In the table (**5**.10), the first column contains the number of nodes, while in the second and third column the times employed by the CPU to find a solution are reported, as follows:

- in the first situation, the model has been solved by considering all the possible bids simultaneously;

- in the second situation, the model has been sequentially solved by using the type I ascending heuristic procedure.

In the last column the reduction of the execution times obtained by solving the model with the sequential type I ascending heuristic algorithm is reported.

Number of nodes	**CPU ALL (s)**	**CPU H1A (s)**	**REDUCTION A**
10	12.584	2.261	82%
15	60.812	2.970	95%
20	71.289	6.889	90%

Table **5**.10: Average computational times comparison (ascending heuristic)

It can be noticed that the improvement in terms of execution times is very important, for about 90% in all cases when the type I ascending heuristic is employed to sequentially solve the BGP.

Analogously, in the table (**5**.11), the first column contains the number of nodes, while in the second and third column the times employed by the CPU to find a solution are reported, as follows:

- in the first case, the model has been solved by considering all the possible bids simultaneously;

- in the second case, the model has been solved by using the sequential type I descending heuristic procedure.

In the last column, the reduction of the execution times obtained by solving the model with the sequential type I descending heuristic algorithm is quoted.

Number of nodes	CPU ALL (s)	CPU H1D (s)	REDUCTION D
10	12.584	3.254	75%
15	60.812	7.470	88%
20	71.289	12.768	82%

Table **5**.11: Average computational times comparison (descending heuristic)

Hence, when the type I descending heuristic is employed to sequentially solve the BGP, the improvement in terms of execution times is lower respect to the previous case, when the type I ascending heuristic is used, but however more than 80%.

We can also provide the gap between the optimal solution and the solutions obtained when the sequential type I heuristic solving procedures are employed.

In all the running instances for the type I sequential ascending heuristic the same optimal solutions as in the case of exact solving with all bundles are obtained. When the type I sequential descending heuristic is used, the solution of the instances is rarely the same with the exact optimal solution, but often the solution is not so close to the latter one.

In the table (**5**.12), the average relative gap of the previous cases is provided. The two columns contain the solution gaps obtained when the sequential ascending heuristic procedure and descending heuristic procedure, respectively, are employed for solving the BGP.

A comparison can be also made directly between the two sequential type I heuristic procedures. As we can see from the tables (**5**.10) and (**5**.11), the computational times obtained when the sequential ascending

GAP H1A	**Gap H1D**
0	0.45655

Table **5**.12: Average relative gap

algorithm is used are almost a half of those obtained by running the sequential descending heuristic.

Therefore, between the heuristic solution algorithms proposed, the sequential ascending heuristic outperforms the sequential descending procedure both from the point of view of the quality of the optimal solution and of the computational times obtained.

For high dimensions, since the input file of all possible bundles (power set cardinality) is extremely huge as the number of auctioned loads in L increased, it is chosen to divide this file into more files, one for each possible cardinality of this set.

The preliminar results obtained are very encouraging and show the efficacy and the efficiency of the developed solving strategies and the utility of the proposed model in terms of tool to support the carriers in their integrated fleet routing and profitable bidding decisions.

Conclusions

This thesis represents a valid study and an accurate analysis of the problems related to the BGP in a combinatorial auction for full truckload transportation.

The major scientific contribution has been to present and define both a mathematical model for the bid generation and evalutation (integrating also the routing of the carriers' fleet) and the heuristic procedures able to solve the BGP on more complex instances.

As future research we intend to develop more heuristic solution methods with the aim to faster solve the BGP and to provide better quality solutions. Other preprocessment procedures of the auctioned loads set may be also constructed in order to overcome the dimension problem caused by the exponential number of bundles. The dependence of the random variables denoting clearing prices of the bundle loads can be successively studied, too. Moreover, even if we proposed a model for the BGP in the truckload transportation combinatorial auctions, we can investigate in which other fields it could be applied.

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