

Spring 2015

Algorithms for bundling and pricing trucking services: Deterministic and stochastic approaches

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By Rodrigo Mesa Arango

Entitled

ALGORITHMS FOR BUNDLING AND PRICING TRUCKING SERVICES: DETERMINISTIC AND STOCHASTIC APPROACHES

For the degree of Doctor of Philosophy

Is approved by the final examining committee:

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4/24/2015

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ALGORITHMS FOR BUNDLING AND PRICING TRUCKING SERVICES:
DETERMINISTIC AND STOCHASTIC APPROACHES

A Dissertation

Submitted to the Faculty

of

Purdue University

by

Rodrigo Mesa Arango

In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

May 2015

Purdue University

West Lafayette, Indiana

For Lina

Thank you for your love

ACKNOWLEDGEMENTS

I am deeply grateful for being mentored by Prof. Satish Ukkusuri, a role model of excellence and dedication. He has encouraged me to always give the best in both personal and professional activities. I am thankful for his support, constructive criticism, and countless development opportunities. By giving me research freedom and debating my ideas he nurtured my creative and independent thinking.

I would like to express my sincere gratitude with my committee members: Prof. Andrew Liu, Prof. Daniel DeLaurentis, and Prof. Fred Mannering. I appreciate their time reviewing my work and providing meaningful comments to improve it. Special thanks to Prof. Fred Mannering for his important guidance in Chapter 2.

Working as a research assistant for the Interdisciplinary Transportation Modeling and Analytics Lab at Purdue has been one of the most rewarding experiences in my career. I would like to thank current and previous lab mates with whom I shared my time there. We had wonderful experiences and exchanged meaningful ideas. Likewise, I would like to thank the members of Purdue ITE, and the IRF.

Before joining Purdue, I had the privilege of interacting with people from different institutions like RPI, Alcaldía de Medellin, Universidad Nacional de Colombia, Universidad del Norte, and UPTC. I want to thank them. Specially Prof. Ivan Sarmiento, advisor for my Master's degree.

There would be no sufficient space to describe the appreciation that I feel for my wife, so I am not writing it here. I will just say thank you for your love. Similarly, my family has played an extremely important role supporting my goals. Special thanks to my mother and father for their dedication and support. Thank you to the loved ones who have passed away, you are always remembered. Likewise, thank you to my siblings, family-in-law, aunts, uncles, cousins, and other family members, to my friends, and Lupita.

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ABSTRACT

Mesa-Arango, Rodrigo. Ph.D., Purdue University, May 2015. Algorithms for Bundling and Pricing Trucking Services: Deterministic and Stochastic Approaches. Major Professor: Satish V. Ukkusuri.

Bundling and pricing trucking services is an important strategic decision for carriers. This is helpful when they consider the incorporation of new businesses to their networks, look for economic and optimal operations, and develop revenue management strategies. Reverse combinatorial auctions for trucking services are real-world examples that illustrate the necessity of such strategies. In these auctions, a shipper asks carriers for quotes to serve combinations of lanes and the carriers have to bundle demand and price it properly. This dissertation explores several dimensions of the problem employing state-of-the-art analytical tools. These dimensions include: Truckload (TL) and less-than-truckload (LTL) operations, behavioral attributes driving the selection of trucking services, and consideration of deterministic and stochastic demand. Analytical tools include: advanced econometrics, network modeling, statistical network analysis, combinatorial optimization, and stochastic optimization. The dissertation is organized as follows. Chapter 1 introduces the problem and related concepts. Chapter 2 studies the attributes driving the selection of trucking services and proposes an econometric model to quantify the shipper willingness to pay using data from a discrete choice experiment. Chapter 3 proposes an algorithm for demand clustering in freight logistics networks using

historical data from TL carriers. Chapter 4 develops an algorithmic approach for pricing and demand segmentation of bundles in TL combinatorial auctions. Chapter 5 expands the latter framework to consider stochastic demand. Chapter 6 uses an analytical approach to demonstrate the benefits of in-vehicle consolidation for LTL carriers. Finally, Chapter 7 proposes an algorithm for pricing and demand segmentation of bundles in LTL combinatorial auctions that accounts for stochastic demand. This research provides meaningful negotiation guidance for shippers and carriers, which is supported by quantitative methods. Likewise, numerical experiments demonstrate the benefits and efficiencies of the proposed algorithms, which are transportation modeling contributions.

CHAPTER 1. INTRODUCTION

1.1 Introduction

Understanding the complex interactions of freight transportation systems is important for several stakeholders, i.e., shippers, carriers, researchers, transportation agencies and policy makers. However, this is a difficult task given the multiplicity of actors with different economic interactions, operations, policies, and objectives. Additionally, the availability of freight-related data is very limited due to the proprietary nature and complexity of freight transportation systems. Yet, there is a significant need to develop new paradigms for freight transportation and a great need to have a rigorous understanding of the behavior, operations, and strategies of actors in freight transportation markets.

Trucking is the most important mode in freight, which accounts for 29% of the for-hire-transportation market share (USDOT 2012). Trucking share is higher than the joint share for the second and third modes, i.e., air (16%), and rail (8.0%). There are two distinguishable actors in the trucking market: Shippers (demand), and carriers (supply). Shippers require moving their goods in lanes, i.e., flow of shipments between different geographies. Carriers (or transporters) own and operate transportation assets, which allow them to provide transportation services that satisfy shipper necessities.

A negotiation process (Figure 1.1) starts when the shipper asks carriers for quotes to transport its shipments. The shipper may require quotes for one or several lanes and these quotes can include different combinations (bundles) of lanes with unique prices. The carrier has to build these bundles and accompany them with attractive prices that also represent acceptable increased profits for its company. Then, bundles are analyzed by the shipper who selects the more attractive ones. Later on, it assigns lanes in the awarded bundles to the corresponding carriers, who have the right to serve them at quoted prices.

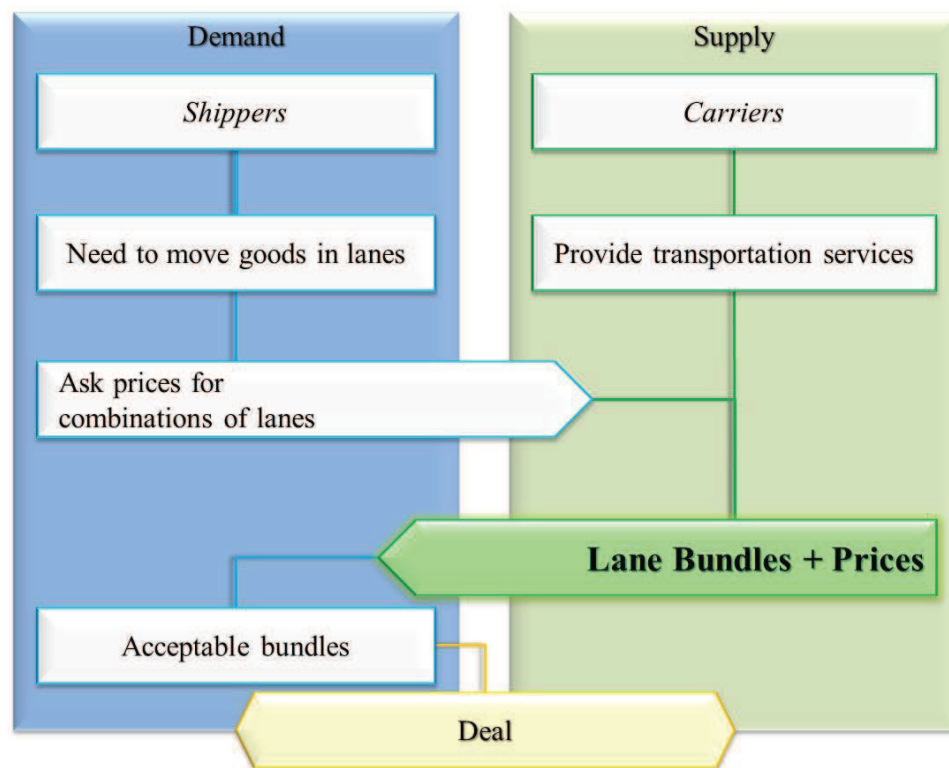


Figure 1.1 Truck service negotiation.

This dissertation focuses on developing methods to construct and price these bundles. Three elements drive bundle construction (Figure 1.2): 1. Shipper preferences, 2. Type of trucking operation, i.e., truckload (TL) or less-than-truckload (LTL), and 3. Lane flow

uncertainty. These concepts are expanded in Subsections 1.1.1, 1.1.2, and 1.1.3 respectively.

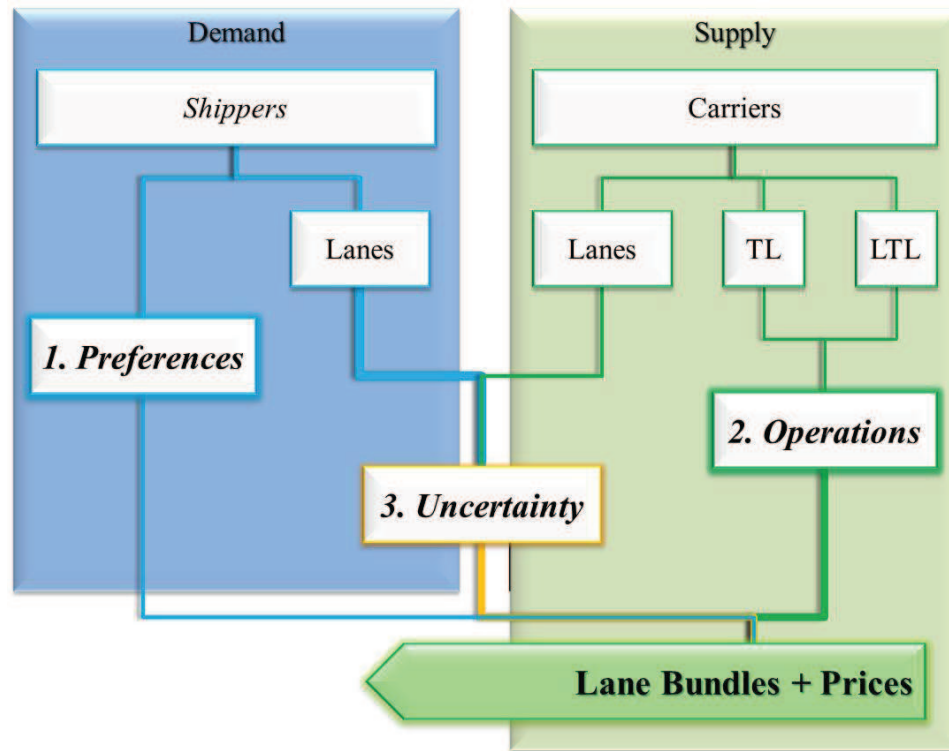


Figure 1.2 Three elements driving bundle construction.

The motivation behind studying trucking service bundling and pricing is presented in Section 1.2. Different types of trucking operations and logistics structures result in different economies that can be exploited to cluster trucking services and develop revenue management strategies with a right balance between operational costs and prices, i.e. offering the right price for the right combination of lanes. These economies are examined in Subsection 1.1.2. Bundle construction is a complex task and complexity increases as more dimensions are added into the problem. This is a very interesting topic from an academic perspective but also has important applications in practice. Freight transportation combinatorial auctions exemplify the necessity of this framework in the

current business environment. Subsection 1.2.1 introduces these auctions and how carriers can benefit by using proper bidding advisory models based on service bundling and pricing. Optimizing asset utilization is not only beneficial to the finances of shippers and carriers but have positive socio-economic repercussions. A summary of these benefits are presented in Subsection 1.2.2. Subsection 1.2.3 presents a literature review that clearly identifies the gaps narrowed by this dissertation. Subsequently, the objectives and contributions of this research are clearly presented in Sections 1.3 and 1.4. Finally, Subsection 1.5 provides guidance through the next chapters of the dissertation.

After providing an overview of this chapter, the three main elements driving bundle construction (Figure 1.2) are expanded, starting by the first one.

1.1.1 Shipper preferences

Shippers are firms that need to move goods, i.e. shipments or consignments, between origins and destination in their supply chains. In this research, they are classified as agents liable for this activity, e.g., freight producers, receivers, or third parties. Some shippers own transportation assets, i.e., fleets and specialized facilities, but others do not. When additional transportation capacity is required by the former shippers they outsource services from carriers. The latter shippers, who focus on their core businesses rather than transportation, procure these services when it is required. The freight transportation choice set available to shippers includes several modes like air, rail, water, intermodal, etc. Nonetheless, this research focuses on shippers that are captive to trucking, the most popular mode in freight.

In general, the procurement of trucking services requires collecting quotes from carriers and selecting the best option. Therefore, carriers are responsible for developing

offers that are both, attractive to the shipper and profitable to themselves. But how is an attractive offer defined? Shippers have different valuations for the lanes that need transportation services. These valuations represent the willingness to pay (WTP) or maximum amount a shipper would pay for each lane. In many circumstances the shipper explicitly states this value in the negotiation saying it will pay no more than the amount v_k for shipments served in a lane k . However, there are circumstances when this information is not explicitly available to the carrier, who must infer it, e.g., using econometric techniques, or assume it, i.e., trusting in its own criteria.

This information is important for bundle design because each bundle is a cluster of lanes related to a unique price that will be charged to every shipment in it. The carrier can price their bundles either using cost-based or value-based approaches. The former estimates price as a margin of service cost and the latter based on the preferences of the client. In general, value-based pricing constitutes a more assertive way of pricing. In the context of lane bundling this concept is stated as follows. If bundle price is higher than the shipper WTP for any included lane, the shipper will reject the bundle as it would not pay such amount. On the other hand, if WTP for each bundled lane is less than or equal to the bundle price, the bundle will be considered by the carrier. Any bundle has to be priced (at most) at the lowest valuation for any included lane. For example, Figure 1.3 exemplifies a shipper with 4 lanes related to geographies in the Midwest of the United States of America. They are sorted in decreasing order with respect to its WTP, i.e., $v_1 \leq \dots \leq v_4$. Following the bundling rule stated before, every bundle (or combination of lanes) should be priced at most at the amount related to the lane with lowest shipper WTP. For example, a bundle i including all lanes $\{1,2,3,4\}$ will be priced at $p_i \leq v_1$ because

lane 1 has the lowest valuation. The same happens with any combination of lanes including lane 1. This example presents 4 pricing possibilities $p_i, p_{ii}, p_{iii}, p_{iv}$ which are bounded above by the WTP of the lane with the lowest value. Following this example, the highest price for a bundle would be $p_{iv} = v_4$ in the case where only lane 1 is bundled, i.e., single-lane bundle {1}.

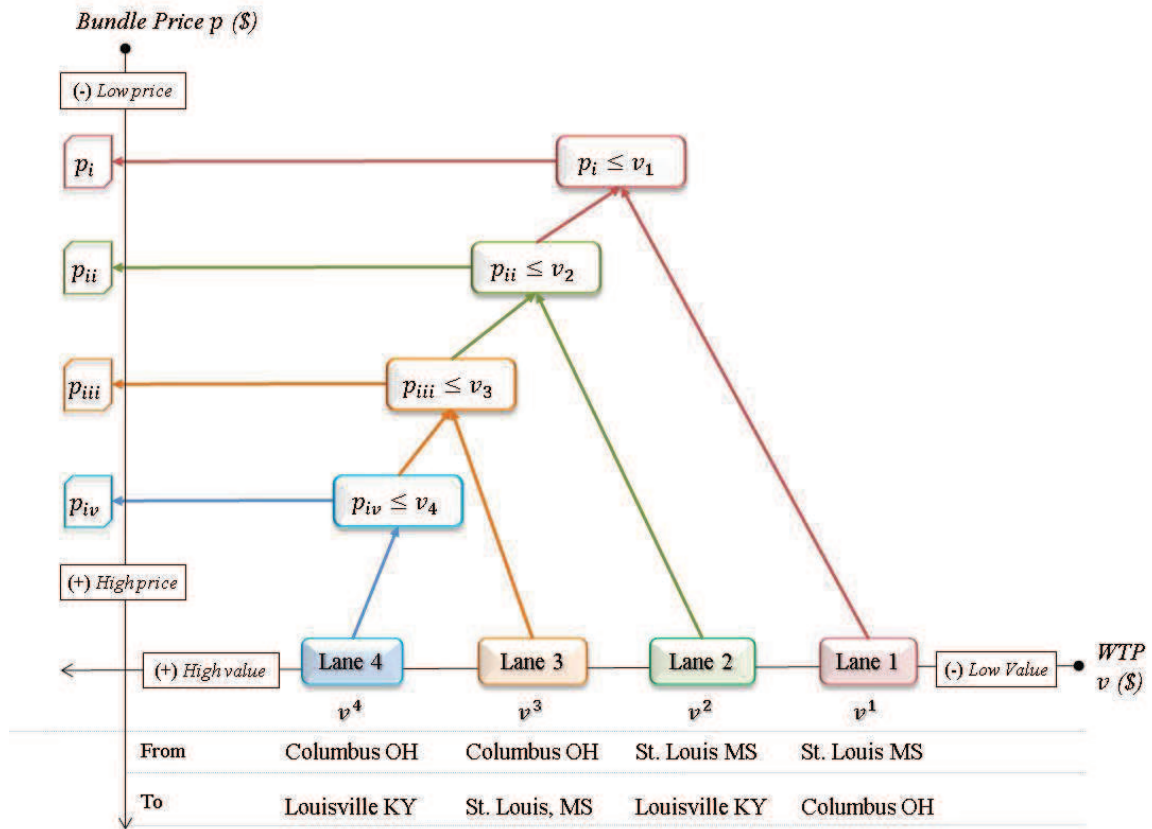


Figure 1.3 Example: relationship between lane WTP (shipper) and bundle price (carrier).

Inferring shipper valuation requires an appropriate understanding of truck service selection behavior. Certainly, price is the most important attribute to determine whether to select a service or not. But it is not the only one. There are attributes that can make a service more attractive even if it is more expensive than the competition. As shown in Subsection 1.2.3, there is scant information about this behavior, which motivates the

development of a model to understand it. Such model will guide carriers when they require inferring lane WTP.

Shipper preferences are critical for bundle design. Shipper behavior significantly affects the income of the carrier, who has to offer high prices that generate profits but are low enough to be attractive for the shipper. Furthermore, designing economic operations reduces operational costs giving more flexibility to price different combinations of lanes.

Different economies are achieved by different types of operations, the second element driving bundle construction (Figure 1.2).

1.1.2 Trucking operations: truckload and less-than-truckload

Complementarities and synergies contribute to the economic prosperity of freight transportation and logistics firms. According to Sheffi (2013), competitive advantages in the freight transportation sector are accomplished by four types of economies.

- (i) Economies of scale: Achieved when the freight flow in a lane is high enough to operate and utilize large vehicles, which reduces the unitary shipment cost.
- (ii) Economies of density: Achieved when several low-flow lanes have similar origins and destinations and can be consolidated in order to enforce economies of scale.
- (iii) Economies of frequency: Achieved when large amounts of freight frequently enter/leave a specific location. This reduces idling cost.
- (iv) Economies of scope: Achieved when it is possible to find follow-up loads that reduce the fraction of shipment unitary cost related to empty repositioning.

Recognizing these economies is important to characterize the benefits related to each type of trucking operation: truckload (TL) and less-than-truckload (LTL), which are reviewed next, starting with TL.

TL companies are well recognized by their flexibility. They serve direct shipments and are usually compared to taxis in passenger transportation. Undeniably, TL is the most popular type of operation for the most popular mode in freight, i.e., trucking. Setar (2013a, and 2013b) estimates that TL accounts for 61% of the 2013 US general trucking industry revenue (\$193.4 Billion). The cost structure of these firms is significantly impacted by economies of scope (Caplice 1996, Jara-Diaz, 1981, and 1983, Chapter 6) and frequency (Sheffi, 2013) as a consequence of empty trips, which result from freight imbalances.

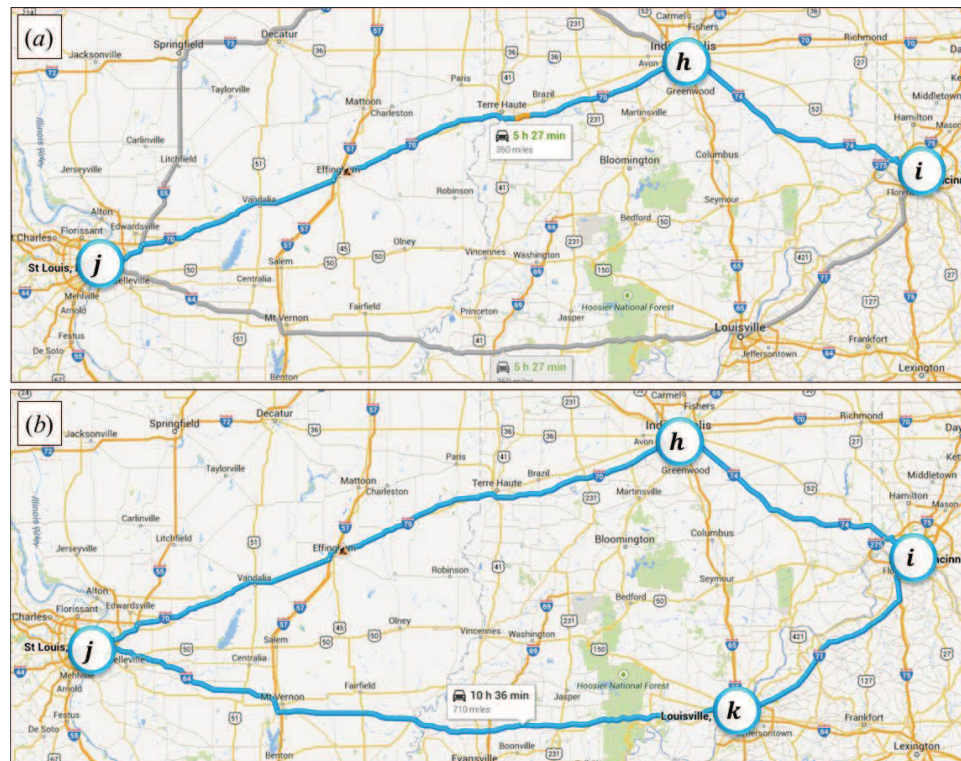


Figure 1.4 Example: economies of scope.

Lane bundling is important for TL carriers in order to achieve economies of scope because they can combining follow up loads that minimize the cost per loaded shipment. Backhauls are intuitive examples of economies of scope. Likewise, trip-chains exemplify this concept. For example, assume a carrier serving a lane between Columbus OH (i) and St. Louis MS (j) over a route through Indianapolis IN (h) (Figure 1.4(a)). The price charged to a shipment in lane $i \rightarrow j$ [lane 1] must compensate the total cost of the round trip $i \rightarrow h \rightarrow j \rightarrow h \rightarrow i$. If a new business occurs in lane $j \rightarrow i$ [lane 2] then this tour keeps a very similar cost while receiving two sources of income [lanes 1 and 2] and, hence, higher profits. This is the economic advantage of backhauls. Furthermore, if the new business is found in another lane, e.g. St. Louis MS (j) to Louisville KY (k) [lane 3], a new trip chain $i \rightarrow h \rightarrow j \rightarrow k \rightarrow i$ (Figure 1.4(b)) with very similar total cost can also be served with more revenues [lanes 1 and 3] and potentially higher profits. However, notice that such economies are not achieved if, for example, the new lane is $i \rightarrow k$ [lane 4] because they will have to be served by independent routes ($i \rightarrow h \rightarrow j \rightarrow h \rightarrow i$ and $i \rightarrow k \rightarrow i$), i.e., they do not complement each other. Economies of frequency are captured when the flows of bundled lanes are similar, if there is an offset between them, then the idling truck should be repositioned elsewhere. But, how LTL differentiate from TL operations?

LTL operation uses a network of facilities to collect, consolidate, and deliver shipments. So, they are fundamentally different and more complex than TL operations. Although the TL market is highly competitive, a smaller number of firms compete in the LTL one. The high investment cost associated with establishing a LTL network limits the number of players in this submarket. An analogy of LTL for passenger transportation

would be transit systems, e.g., subways or buses. Consolidation is crucial to achieve economies of scale and density (Caplice 1996, Jara-Diaz 1981, Jara-Diaz 1983, Chapter 6). According to Caplice (1996) there are three types of consolidation: (i) at the origin, i.e., waiting for an appropriate size to be shipped; (ii) inside vehicles, i.e. sharing transportation with shipments from other origins; (iii) and/or in terminals, e.g. hub-and-spoke operations.

LTL carriers serve low-weight shipments, i.e., between 151 *lb* and 20,000 *lb* . Shipment volume is also important when shipping LTL freight. In general, logistics service providers handle this using a dimensional weight that accounts for shipment density. They are computed dividing shipment volume, i.e., length x width x height (in^3) by a dimensional factor (in^3/lb). Such factors are defined from an ideal shipment density and vary among carriers, e.g. 125 FedEx, 139 DHL, and 194 USPS. Shipments are prized considering the highest value between actual and dimensional weight.

LTL carriers collect these shipments and deliver them through a network commonly known as line-haul (Erera et al. 2008), or line-operations (Powell and Sheffi, 1989) network. This is a disassortative hub-and-spoke network (Figure 1.5), where end-of-line terminals (EOLs) describe the spoke nodes and breakbulk terminals (BBs) the hubs nodes. In some cases relay nodes (where drivers are relieved) are considered as part of the network. Drivers can be changed in any type of terminal though. Furthermore, arcs are described as long-haul feeders (Lin et al. 2009), where transportation assets are assigned to move freight. An arc exists whenever a BB is origin or destination for movements. Arc traversing time is usually shorter than the maximum legal driving time for a commercial vehicle.

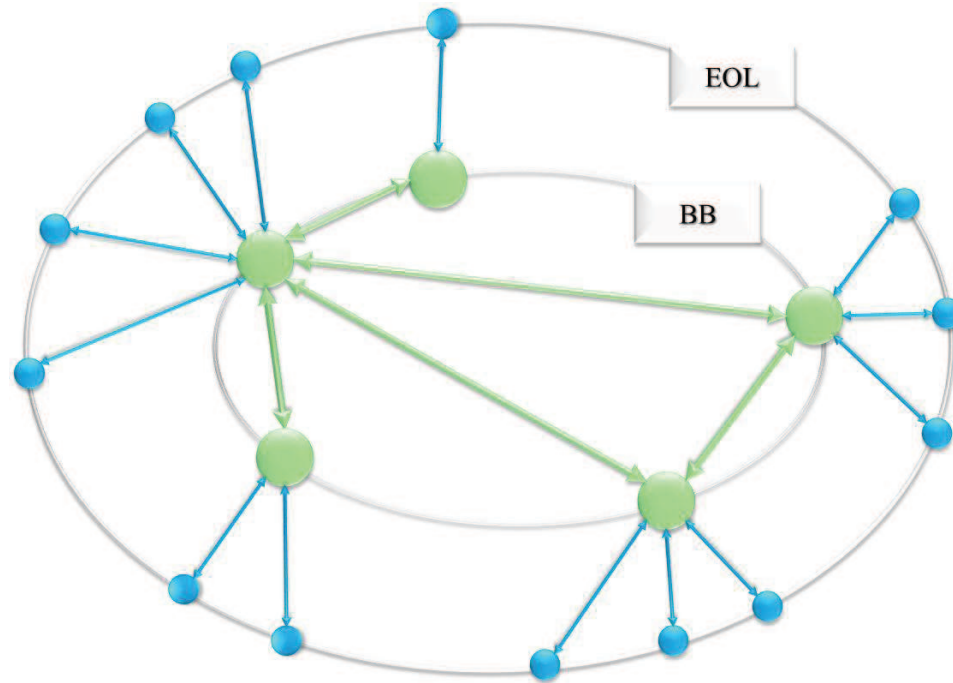


Figure 1.5 General Illustration of the LTL Network

EOLs serve small geographies and BBs serve the aggregation of areas encompassing several EOLs. EOLs are usually associated to their closest, or primary, BB. Shipments are collected periodically, sorted, and loaded to outbound trucks at the EOLs. These trucks are directed to the corresponding BB that also consolidates freight from other related EOLs and BBs. Here, shipments are once again unloaded, sorted and reloaded for the next haul. The amount of freight at each BB is large enough to send full trucks to other BBs. The next haul can be either to a destination EOLs, i.e., for final delivery, or other BBs, i.e., to continue in transit before final delivery. A typical shipment follows the path $\text{origin} \rightarrow \text{EOL}(\text{origin}) \rightarrow \text{BB}(\text{origin}) \rightarrow \text{BBs}(\text{intermediate}) \rightarrow \text{BB}(\text{destination}) \rightarrow \text{EOL}(\text{destination}) \rightarrow \text{destination}$. The number of transferences at intermediate BB depends on factors like reducing repositioning and handling cost, increasing asset

utilization, and guaranteeing a predefined level of service (delivery time). In LTL terminology, a *Load Plan* describes the paths of shipments between each pair of terminals. As an operational constraint, all freight moved between a pair of terminals must follow the path in the *Load Plan*.

When there is enough load to send full trailers, LTL carriers can schedule direct services (TL style) that omit the instructions of the *Load Plan*. In practice, this often happens between BB(origin) and EOL(destination). Although direct services between EOL(origin) and BB(destination) are possible, they are infrequent. Finally, carriers do not consider direct services between EOLs because they are rare. About 15% of shipments are performed directly (Powell and Sheffi, 1989).

28-ft trailers, a.k.a. pups, and 48-ft vans are characteristic assets in LTL operations. In general 28-ft trailers are preferable because the capacity of a tandem is almost equivalent to a 48-ft van, and it is easier to consolidate and send full single 28-ft trailers to a destination. Thus, operations are simplified to drop-and-hook maneuvers rather than loading/unloading procedures. Demand imbalances make empty repositioning inevitable and there are different types of repositioning: regular empty trucks or trailers (single or coupled), combination of empty and full trailers, and tractor movements with no containers (usual in intermodal systems). In practice, firms state minimum truck frequencies that have to be maintained between BBs, e.g., Powell and Sheffi, (1989) study a firm where 2 to 3 trailers per week are dispatched from terminals.

Although LTL are rigid system, in-vehicle consolidation strategies can be developed by hybrid carriers to bundle services and take full advantage of both economies of scope

and scale. Such alternative is explored in this dissertation and its benefits are demonstrated in Chapter 6.

In summary, profitable bundles are constructed by properly balancing revenues and costs. Expected revenues are determined by a pricing scheme that accounts for shipper preferences, and operational costs are directly related to the type of trucking operation and its corresponding economies. Out of these two elements (Figure 1.2), there is a third and final component driving bundle design.

1.1.3 Lane flow uncertainty

Carriers have to consider two types of lanes when bundling and pricing services, i.e., those that needed to be served (communicated by the shipper in the negotiation process), and those that are currently being served (to other shippers). The lanes that need to be served are important because they determine new sources of income for the carrier and can be combined in different ways to achieve the economies described in the previous subsection. Current lanes are important for TL carriers because they can be used to determine additional complementarities that account for economies of scope. On the other hand, they are important for LTL operations because they determine the current available capacity in the LTL network.

However, flow in lanes (i.e., number of shipments or weight per unit of time between an OD pair) fluctuates significantly independent of the type of lane. This adds unwanted uncertainty to the bundle construction process.

Carrier finance can be harmed significantly if such uncertainty is not overseen at the bundles are planned. Demand communicated in the negotiation process is obtained from projections developed by the shippers. Unfortunately, the actual realizations of flow are

considerably different to the forecasted ones (Caplice and Sheffi, 2006). Usually, shippers assign carriers the right to serve lanes in awarded bundles. This means that the winning carrier will have priority to serve shipments in an awarded bundle at the quoted price when demand realizes. However, if demand does not realize as expected, the carrier is not contacted and no income is perceived. Although this is an undesirable phenomenon, it is frequent, accepted by both parties, and occurs for several reasons.

Lane flow is the result of economic interactions between freight agents. This flow is highly impacted by disruptions in the supply chain encompassing the lane. Unfortunately, disturbances propagate quickly in this context due to the underlying network structure of freight businesses. Although spatiotemporal disruptions occur for many different reasons, some examples include: seasonal changes (e.g., holidays or harvest), macroeconomic impacts (e.g., economic recessions or booms), disruptions in infrastructure systems (e.g., inclement weather or traffic effects), among others.

Although the carrier cannot predict these variations with total accuracy, it can estimate scenarios and probabilities related to certain demand realization. A proper utilization of this information will help it to develop better bundles.

After reviewing the main three elements driving the design of bundles and prices for trucking services, the next subsection shows its real world implementation, clearly demonstrates the benefits of this strategy, and shows the modeling gap in literature that motivates this dissertation.

1.2 Motivation

This section clearly presents the incentives that motivated the development of this dissertation. First the real world application of the bundling/pricing problem studied in

this research is contextualized, i.e., trucking combinatorial auctions (Subsection 1.2.1). Then socioeconomic benefits associated with bundling trucking activities are presented, which is an additional motivation to study this problem (Subsection 1.2.2). Finally, literature is reviewed seeking for models that address the bundling/pricing problem. It is found that these models (mainly developed in the context of combinatorial auctions) have limitations that motivate improvements developed in this research.

1.2.1 Real world application

Trucking combinatorial auctions (CA), an evolving market mechanism used to assign freight contracts to carriers, constitute the main application where truck service bundling and pricing is implemented in practice. This framework has shown significant cost reductions for both shippers and carriers. CA have been successfully implemented by several firms, e.g., Home Depot Inc., Wal-Mart Stores Inc., Compaq Computer Corporation, Staples Inc., The Limited, K-Mart Corporation, Ford Motor company, Reynolds Metal Company, Sears Logistics Services, among others (De Vries & Vohra 2003, Elmaghraby & Keskinocak 2004, Moore et al. 1991, Porter et al. 2002, Sheffi 2004). The main characteristics of trucking CA are presented next.

A trucking CA is a reverse auction, i.e., auctioneers are buyers and bidders are sellers. Thus, a shipper auctions freight lanes, i.e., shipments to be transported between geographically distributed OD pairs, and a group of carriers bid for them. In general, the scope of these ODs corresponds to long hauls at the national level. The shipper explicitly communicates its WTP for every lane as reservation prices. The main characteristic of a CA is that, rather than bidding for individual lanes, carriers can bid for bundles or combinations of them. This is attractive to the shippers because the price of a shipment

served as part of a bundle is usually lower than or equal to the price of serving it individually. Once all the bids are collected, the shipper solves the Winner Determination Problem (WDP) to match lanes with the most appropriate carriers. Extensive research has been conducted to formulate and solve the WDP in CA (Abrache et al. 2007, Caplice & Sheffi 2006, Ma et al. 2010, Sandholm 2002). There are single-round and multiple-round TL CAs. In a single round CA, the shipper assigns the right to haul shipments to the winning carriers at the quoted prices. In a multiple round CA, the shipper updates reservation prices according to the best prices on each lane and carriers are asked to bid again. This repeats for several rounds, regularly 2 and no more than 4 rounds. But, what are the challenges for carriers in these auctions?

Carriers are responsible for building and submitting bids that are attractive to the shipper. Competitive prices are usually achieved when the quoted lanes are complementary to the routes operated by the carrier. Trucking CA are frequently conducted in the procurement of TL services. Previous researchers propose bidding advisory models to solve this problem (Lee et al. 2007, Song and Regan 2003, and 2005, Wang and Xia 2005). Although TL CAs represent potential win-win situations for shippers and carriers, the construction of efficient bundles is a challenging task. Some auctions involve hundreds of lanes and the number of bundles grows exponentially with respect to lanes (Song and Regan, 2003 and 2005). Many carriers with limited analytics skills use behavioral rules, e.g., bundling only backhauls and bundling as many lanes as possible from a particular location, but the rigorous construction of good-quality bundles requires the implementation of analytical techniques. As will be show in Subsection 1.2.3 the techniques used for bundle construction in previous research have a number of

limitations that motivate the development of the novel algorithms presented in this dissertation.

Professionals working for carriers participating of CA can significantly benefit from efficient advisory models that facilitate service bundling and pricing in order to submit good quality bids that incorporate the three elements described before (Figure 1.2).

Moreover, although TL CA are widely recognized in shipper/carrier interactions, few is known about its implementation and challenges for LTL systems. Therefore, an additional motivation for this research is properly characterizing CA in the LTL context.

Furthermore, society indirectly benefits by the use and implementation of revenue management strategies based on demand bundling or clustering. Such benefits are another motivation to study this phenomenon and are illustrated in the next subsection.

1.2.2 Socio-economic benefits

Bundling is closely related to the concept of clustering. Governments recognize the economic importance of logistics clusters and increasingly provide incentives for firms to (re)locate into these facilities. However, this is a slow process. Sometimes it is not even an alternative for many shippers and carriers that face enormous relocation costs, off-shoring issues, and potential detriment of relationships with clients. Additionally, logistics clusters might not be a feasible option because they have not emerged naturally, they are not a priority for local governments, or they are not suitable for unstable economic landscapes. In these cases, firms that can mimic the advantages of logistics clusters while increasing revenues for transporters and adding value to their clients can significantly impact the economic environment of the region they serve. Such benefits

can be achieved by the application of bundling and pricing strategies as those presented in this research.

As shown before, the economies of bundling increase as empty trips and unused capacities are reduced. In practice, firms recognize these benefits. Companies like Best Buy, Coca-Cola Supply LLC, JB Hunt Transport, Johnson & Johnson, Walmart Stores, Inc, among others, have participated of the Empty Miles program (VICS, 2014) to share unused transportation capacity and reduce empty-trip inefficiencies (Belson, 2010). In 2009, the chain of department stores Macy's cooperated with shippers and carriers to reduce 1,500 empty trips in the US. In average, they saved \$25,000 transportation costs annually for each shared lane (VICS, 2009). JCPenney, another important department-store chain, shared 41,000 backhauls that saved them \$8.1 Million between 2008 and 2009 (Andraski, 2010). Schneider National, the largest private TL carrier in North America, increased dedicated backhaul revenue by 25% on specific accounts thanks to this initiative (VICS 2009).

Unfortunately, empty trips are not rare for trucking operations. 25% of the 2010 truck-kilometers in Europe where traveled empty (De Angelis, 2011). Reduction of empty trips can significantly benefit society because they are related to serious externalities like emissions, traffic congestion, noise, accidents, and wear of roads. The monetary savings obtained by Scheider National also saved them 5,554 gallons of diesel fuel that eliminated 61.65 tons of carbon dioxide, 147.24 tons of articulate matter and 1.47 tons of nitrous oxide. Similarly, JCPenny eliminated 9,750 tons of CO₂ by utilizing 20% of its empty miles in 2009 (4 million miles) and 6% (1.3 million miles) in 2008. One strategy to mitigate these externalities is to utilize unused capacity inside the trucks (EC-

DGET, 2006; OECD, 2003; Sathaye et al., 2006; TFL 2007). Understanding and promoting economic mechanisms that improve truck utilization while enhancing profits for shippers and carriers can accelerate the acceptance and implementation of such strategies.

The pragmatic need and socio-economic benefits of bundling and pricing motivate the development of modeling frameworks that appropriately handle the three elements driving this strategy. However, several limitations are encountered in models that address this problem in literature.

1.2.3 Modeling gaps in literature

This section reviews relevant literature for truck service bundling and pricing, which identifies the existing modeling gaps in literature. These gaps are fulfilled by the efforts developed in this dissertation. First, the lack of paradigms to properly understand shipper preferences regarding trucking services is highlighted. Then, additional evidences to improve current bundling models in literature are shown.

User preferences and the corresponding WTP have been widely studied by transportation researchers to quantify the subjective value of time perceived by passengers traveling in a transportation network. The WTP for other attributes related to these services has received additional attention in the literature (e.g., Balcombe et al., 2009; Basu and Hunt, 2012; Carlsson, 2003; Hensher, 1997; Hess et al., 2007). In contrast to passenger transportation, the WTP for attributes related to freight transportation services have received less attention. Recent works that study this problem mainly focus on freight trip choice (Hensher et al. 2007, Pucket and Hensher 2008, and Li and Hensher 2012), and the competition between different modes in freight (Anderson,

et al. 2009; Banomyong, and Supatn, 2011; Bray, et al. 2004; Brooks, et al. 2012; Danielis and Marcucci, 2007; Fries et al., 2010; Masiero and Hensher, 2010, 2011, and 2012; Patterson et al. 2010; Puckett, et al. 2011; Train and Wilson, 2008; Zamparini, et al. 2011). However, limited attention has been paid to the competition within the trucking mode. The work by Cavalcante and Roorda (2013) represents the closest approximation to this problem. However, they do not cover it entirely because their objective is to illustrate a meaningful data collection project rather than to develop and analyze a behavioral model. So, there is no work that estimates the shipper WTP for attributes driving trucking service selection in this context exclusively. It can be intuitively argued that shippers only consider the lowest-price option when procuring trucking transportation. So, why is it relevant to study other attributes?

There is evidence of shippers assigning contracts to carriers that are not necessarily the cheapest ones. For example, Caplice and Sheffi (2006) show that some shippers on average forgo 50% of potential procurement savings in order to prioritize service requirements and other business constraints, i.e., they sacrifice 7% out of 13% average cost savings to maintain business constraints and performance factors. Similar insights are obtained from the work by Moore, et al. (1991), and Elmaghraby and Keskinocak (2002). Murphy and Hall (1995) recognize the importance that price and other attributes gained after the US motor carrier regulatory reform in 1980. While it has been acknowledged that price may not necessarily be the only criteria, the question of what pragmatic attributes are considered by shippers in the selection of trucking services is still not clearly answered.

Pragmatism is very important for managerial and operational decisions. Freight-related choices are usually explained by important holistic variables like on-time reliability, damage risk, security risk, etc. However, this information is not explicitly available for operational choices. Instead, such concepts are hidden in information transferred during trucking transactions, e.g., reliability is ensured by the monetary refund offered if the service is not provided properly.

At this point, the first gap in literature can be clearly stated as follows.

- *Gap 1. There is no work in literature studying shipper preferences towards the selection of trucking services when trucking is the only mode considered.*

Additionally, narrowing this gap implies stating a set of pragmatic attribute explaining truck service selection, and computing the WTP for these attributes. Next, gaps related to modeling trucking-service bundling and pricing (mainly for freight auctions) are detected.

As shown in Subsection 1.2.1, truck service bundling and pricing has been studied by bidding advisory models in TL CA. The few bidding advisory models available in this literature are reviewed next.

Song and Regan (2003) is one of the pioneering works in this area and the work by Song and Regan (2005) improves some limitations from their former research. These papers introduce key concepts for TL CA, e.g., lane valuation and economies of scope. They use an optimization-based framework that minimizes costs related to truck repositioning, i.e., empty movements, to construct bids. After defining bundles, prices are determined as a margin of the costs (cost-based pricing). Additionally, these models restrict bundles to serve either all the demand in a lane or nothing.

Wang and Xia (2005) propose a heuristic method for bid construction minimizing empty trip costs with the help of a novel synergy metric. However, pricing is simplified and relaxed. Moreover, lanes are selected as binary variables without flexibility to select fractions of demand.

Lee, et al. (2007) present an advisory model that finds a single optimal bid that maximizes carrier profit, i.e., the difference between best lane prices and bundle costs in the current round of the auction. Considering current best lane price to compute profits is not consistent with a CA context, where all items in a bundle must keep the same price. Similar to other research, lanes are selected in a discrete fashion. Additionally, the outcome of this model is risky for the carrier because it is an optimal subset of all potential bids but adds no redundancy to the bidding process (important if other carriers have better prices for common lanes).

Although these are important bundling models, they have several limitations. The first two are related to pricing and demand segmentation. What are the limitations of oversimplifying pricing?

As Nagle et al. (2011) highlight, cost-based pricing is problematic for profit maximization and counterintuitive from a managerial perspective. In general, value-based pricing is a better option. Coyle et al. (2011) state that value-based pricing is more beneficial for trucking industries than the traditional cost-based tariffs. Similarly, Randall et al. (2010) show how the use of value propositions is increasing in the trucking industry. Thus, another limitation related to previous research can be stated.

- *Gap 2. There is no truck-service bundling/pricing model in literature that proposes a value-based pricing approach when bundling trucking services.*

The second limitation is related to the impossibility of segmenting demand within bundles. In new trucking CA, carriers are allowed to combine lanes and determine the volume of demand that they are willing to serve within each bundle. This gives carriers the flexibility of bidding for volumes that increase their economies and allows shippers to increase the robustness of their businesses by splitting high-volume lanes into several carriers. Since bidding advisory models in literature do not consider this feature, the next gap can be stated as follows.

- *Gap 3. There is no truck-service bundling/pricing model in literature that considers demand segmentation within bundles.*

Although lane flow uncertainty plays an important role in the design of profitable bundles and prices (Subsection 1.1.3), it is not considered in the models available on literature. These models assume deterministic behavior for lane demand which represents potential losses when demand does not realize as expected. This justifies the fourth gap in literature.

- *Gap 4. There is no truck-service bundling/pricing model in literature that considers stochastic lane flow.*

The last gaps were identified after reviewing models developed for TL CA, which itself highlights a more fundamental gap stated next.

- *Gap 5. There is no truck-service bundling/pricing model for LTL operations.*

Thus, the developments of new LTL models should also overcome the limitations highlighted for TL models.

So far, the truck-service bundling/pricing problem have been contextualized and motivated. Likewise, gaps in previous literature were identified. Based on these gaps, the next section articulates the objectives of the dissertation

1.3 Objectives

The main objective of this dissertation narrow the modeling gaps in literature by developing a set of algorithms for bundling and pricing trucking services that properly account for shipper preferences, carrier operations, and lane flow uncertainty. The specific objectives are:

- *Objective 1.* Understand shipper preferences toward truck-service selection using econometric analysis.
- *Objective 2.* Develop a framework for demand clustering in TL networks based on historical data of lane flows and prices.
- *Objective 3.* Develop a model for demand bundling in TL networks that considers value-based pricing, and demand segmentation.
- *Objective 4.* Develop a model for demand bundling in TL networks that considers value-based pricing, demand segmentation, and stochastic lane flows.
- *Objective 5.* Demonstrate the economic benefits of routing strategies considering in-vehicle consolidation in the development of bundles for trucking service.
- *Objective 6.* Develop a model for demand bundling in LTL networks that considers value-based pricing, demand segmentation, and stochastic lane flows.

1.4 Contributions

This dissertation provides the following contributions to the transportation community and the specific field of freight and logistics.

Chapter 2

- Understand the behavior behind the selection of trucking services by shippers that move truck shipments.
- Postulate a set of pragmatic attributes to explain truck-service selection.
- Quantify the shipper WTP for these attributes.
- Provide meaningful negotiation guidance for shippers and carriers based on behavioral modeling.

Chapter 3

- Propose a systematic framework for demand clustering in freight logistics networks.
- Incorporate economic interdependencies among clustered lanes considering network effects.
- Consider historical market prices in the clustering process.
- Integrate uncertainty associated to historical variations on lane prices and volume.
- Develop a computationally efficient method for freight demand clustering.

Chapter 4

- Develop a bundling model for TL services that handles bundle generation and value-based pricing explicitly.
- Specify the amount of flow that the carrier is willing to serve in each bundle.

Chapter 5

- Develop a bundling model for TL services that combines low cost bundles with value-based pricing that maximize profits.
- Determine the TL volume that the carrier is willing to serve within each bundle.
- Incorporate demand uncertainty in the construction of bundles.

Chapter 6

- Demonstrating the benefits of considering in-vehicle consolidation strategies when bundling trucking services.

Chapter 7

- Combine available information to derive the taxonomy of LTL CA
- Address for the first time the bundling/pricing problem from an LTL perspective
- Develop a bundling model based on value-based pricing that properly handles valuation rules.
- Segment demand to define the maximum lane flow that the carrier is willing to serve in each bundle.
- Incorporate demand uncertainty in the construction of bundles.

The following Section guides the reader through the different chapters in the dissertation.

1.5 Dissertation organization

This dissertation is organized as follows. Chapter 1 contextualizes the problem studied in this dissertation, i.e., of bundling and pricing trucking services, motivates its study, states the objectives and contributions. Chapter 2 studies the attributes driving the

selection of trucking services and quantifies the shipper's WTP. Chapter 3 proposes a framework for demand clustering in freight logistic services for direct shipments (TL). Chapter 4 presents a method to price and bundle TL services without considering lane flow uncertainty. This method is improved by the model in Chapter 5, which is able to capture such uncertainty. Chapter 6 demonstrates the benefits of in-vehicle consolidation for LTL related to bundle design. Chapter 7 presents a model to price and bundle LTL services. Finally, Chapter 8 summarizes this work and concludes the dissertation.

CHAPTER 2. ATTRIBUTES DRIVING THE SELECTION OF TRUCKING SERVICES AND THE QUANTIFICATION OF THE SHIPPER'S WILLINGNESS TO PAY

2.1 Introduction

This chapter investigates the selection of trucking services by shippers that require the movement of truck shipments. A set of pragmatic attributes are postulated to describe trucking services. They are used in a stated choice experiment that collects data and preferences from shippers. A mixed logit model is estimated in order to test the attributes and quantifying the shipper willingness to pay (WTP) for them. The results are used to provide meaningful negotiation guidance for truck-related shippers and carriers, a significant contribution to literature in transportation, logistics, and supply chain management. A numerical example illustrates the use of the model.

Knowledge about the WTP for trucking services can benefit several stakeholders. First, this information helps shippers to benchmark their current prices with respect to the average market, which is useful to negotiate contracts, detect cost saving opportunities, updating transportation service providers, forecasting costs for new businesses, and planning and designing transportation networks integrated to their supply chains.

Second, carriers can benefit by developing value-based pricing strategies, which have been widely used in industries such as airlines, groceries, e-markets, etc. Randall, et al. (2010) show that trucking companies are actually using value propositions when offering their services on internet, and Coyle, et al. (2011) highlight the benefits of this strategy over traditional trucking tariffs or cost-based pricing. The work by Özkaya, et al. (2010) is one of the few examples of value-based price modeling in the trucking industry (for less-than-truckload (LTL) services).

Third, results from a truck service selection model and the shipper WTP help researchers and public agencies to improve their understanding of freight transportation markets. This behavior can be incorporated in game theoretic (e.g., Shah, and Brueckner, 2012), and agent-based modeling (e.g., Roorda et al. 2010) frameworks to replicate market interactions and test different policies. Likewise, understanding this fundamental interaction can improve multimodal freight regulatory studies by providing specific details about the pragmatic variables considered by the shippers in the selection of trucking services. This, accompanied with analyses for other modes, might explain part of the unobserved heterogeneity obtained in their underlying models.

In order to understand how shippers select carriers and to quantify the WTP for trucking services, a set of carrier attributes are postulated and presented to several shippers in a stated choice experiment (SCE). This information is complemented with shipper and shipment characteristics to develop a general mixed logit model for carrier selection. The discrete choice model is used to (i) test the statistical significance of the postulated attributes, (ii) estimate their marginal effects, and (iii) quantify the shipper WTP.

This chapter is organized as follows. Section 2.1 introduces and motivates the problem. Section 2.2 reviews literature on shipper WTP and postulates a set of attributes for trucking service pricing. Section 2.3 describes the survey design and sample characteristics. Section 2.4 describes the econometric approach applied. Section 2.5 presents the model estimation and discusses the results. Section 2.6 shows an example of the application of the model. Finally, Section 2.7 concludes the work.

2.2 Literature review

This section presents a literature review of previous works related to the selection of freight transportation services and the corresponding shipper WTP. This illustrates the gap related to trucking service choice on literature. Additionally, attributes that were considered to explain similar choices are summarized in order to postulate the carrier attributes considered in this research.

Several works have contributed to understanding the behavior of shippers and carriers in the context of trip/route choice for truck trips (Hensher et al., 2007; Li and Hensher, 2012; Puckett and Hensher, 2008) and general freight trips (Masiero and Hensher, 2010; 2011; and 2012; Patterson et al., 2010). Thus, the WTP for attributes of the transportation network has been quantified, e.g., travel time, congested time, etc., which is important for appropriate pricing of the system, e.g. toll-roads. There are certain communalities between these works and the selection of trucking services by shippers. However, these works study trip choice, which highly depends on operational characteristics of the transportation system. On the other hand, the selection of carrier by shippers is a more strategic decision that is conceptually and fundamentally related to mode choice.

Carrier selection and the shipper WTP for service attributes has been studied for the choice of freight transportation mode and facility, e.g., port. Moreover, studies that have explored general choices of logistics services are limited to specific geographies. Bray et al. (2004) surveyed shippers to study their WTP for water transportation services in the Ohio River Basin. They provided valuable qualitative conclusions that are not supported by statistical or econometric models. Puckett et al. (2011) investigated the impact of attributes in short sea shipping with a mixed logit model. Train and Wilson (2008) used a mixed logit model to study route/mode choice among six alternatives on the Columbia/Snake river. Anderson, et al (2009) estimated the WTP to avoid delays and increase reliability (frequency of transportation services) in United States ports for maritime transportation. Danielis and Marcucci (2007) evaluated the preferences of a subset of Italian shippers for freight services using randomly generated alternatives. Zamparini, et al. (2011) found the shipper WTP for quality attributes in Tanzania. Banomyong, and Supatn (2011) investigated the selection of third-party logistics (3PL) service providers in Thailand as a function of several attributes. However, they did not quantify the shipper WTP for these attributes. Brooks, et al. (2012) presented an Australian mode choice study that examined land-based transport and coastal shipping. However, many of these studies did not consider trucking-services in the mode choice and none of them studied the choice of trucking-services by shippers exclusively.

The only study that considered choice within trucking services is the work by Cavalcante and Roorda (2013). They used a stated preferences (SP) web-based survey to collect data for motor-freight carrier choice. Since the core of their work is the development of a web-based tool for data collection, a simple multinomial probit model

that does not incorporate unobserved heterogeneity among respondents was used. Likewise, there was no discussion about the effect that these attributes have on the carrier choice process. The corresponding shipper WTP was also not quantified. Therefore, a work that exclusively studies carrier selection and shipper WTP for trucking services using state-of-the-art econometric tools is missing on literature.

Table 2.1 Attributes for mode and service choice in freight transportation

Work	Attributes
Danielis and Marcucci (2007)	Price, time, late arrivals, loss and damage, flexibility, frequency, mode: road only and intermodal
Train and Wilson (2008)	Price, time, reliability,
Anderson et al (2009)	Price, time, reliability
Puckett et al. (2011)	Frequency
Zamparini, et al. (2011)	Time, flexibility, frequency, loss and damage, reliability.
Banomyong, and Supatn (2011)	Price, reliability, assurance, tangibility, empathy, responsiveness, accuracy of documents, EDI and e-commerce services, customer relationship management, customer care, updated freight rates, consolidation provision
Brooks et al. (2012)	Price, time, distance, direction (headhaul/backhaul), reliability
Cavalcante and Roorda (2013)	Price, carrier reputation, response to problems, quality of drivers, follow-up on service complains, billing accuracy, equipment availability, delivery reliability, lost/damaged products, past experience.

Table 2.1 summarizes attributes considered for mode and service choice in previous freight transportation research. Identifying them is important to postulate a set of attributes used for the SCE design and subsequent model development. Attributes related to price, delivery time, reliability, frequency, loss and damage, and flexibility are considered regularly. Other attributes are related to customer relationship, electronic services, e.g., electronic data interchange (EDI), consolidation level, etc. Although in a different context, i.e., trip choice, attributes like experience and carrier assets have shown significant influence in freight-agent decisions (Hensher et al. 2007). However, in many

cases these variables are too coarse to understand the valuation that shippers assign to attributes offered in trucking services. A clear linkage between general freight attributes and those used in the actual shipper/carrier interactions is missing on literature. In this sense, Randall, et al. (2010), used data mining software and a value proposition qualitative framework to obtain insights of the different attributes offered by trucking companies in the internet. They found five essential elements in the current motor carrier industry: (i) time utility: moving freight at specific times, (ii) place utility: cargo types, capacity, and geographic scope; (iii) transaction value management: guaranty, flexibility, EDI capabilities; (iv) value-added extensions: provision of additional managerial and logistic services, e.g., consolidation; and (v) carrier-specific values: firm values. The next section presents the set of attributes used to model carrier selection based on this review. Furthermore, previous research on trucking service selection focuses on attributes of the transportation services but do not consider attributes of the decision maker (shipper) and context (shipment), which is important to develop well defined models that incorporate unobserved heterogeneity. Such attributes are considered in this work and also introduced below.

The next section describes the SCE design and presents summary statistics for selected variables collected in the survey.

2.3 Stated choice experiment design and sample description

This research studies the selection of carriers by shippers that require trucking services. As in any freight-related study, collecting this type of data is extremely challenging because of its proprietary issues. A negligible response rate is expected if shippers are asked specific information about their actions. A SCE overcomes this

limitation by collecting stated preferences that do not compromise confidential information. Attributes for the SCE are chosen after literature review (Section 2.2). The selection of corresponding levels is justified below. The SCE is designed as an approximation of the optimal experiment design proposed by Street and Burges (2007). This section first presents technical characteristics of the SCE design followed by a description of its implementation, i.e., respondent profile, distribution, and data collection.

The experiment is composed by a number of cases (choice sets) N that are presented to each shipper. Each case n is associated to M alternatives (hypothetical carriers), where each alternative m is described by Q attributes, and each attribute q is associated to ℓ_q levels.

Table 2.2 Carrier attributes q and levels ℓ_q in the stated choice experiment

q	Attribute description	ℓ_q	Level description
1	Price	1	30% less than regular
		2	10% less than regular
		3	10% more than regular
		4	30% more than regular
2	Delivery time	1	Minimum accepted
		2	Average accepted
		3	Maximum accepted
3	Fleet Size (Power Units) (carrier specific values)	1	100
		2	1,000
		3	10,000
4	Average model of trucks (carrier specific values)	1	2001
		2	2006
		3	2012
5	Refund if service not provided as agreed (loss and damage)	1	50% price
		2	80% price
		3	110% price
6	Experience with the carrier (customer relationship)	1	No experience
		2	Satisfactory experience
		3	Unsatisfactory experience
7	Type of shipment (consolidation level)	1	Direct (TL)
		2	Consolidated (LTL)
8	Service between origin-destination (OD) (frequency)	1	Regular/Usual
		2	Irregular/Unusual

q	Attribute description	ℓ_q	Level description
9	Flexible to changes in capacity and/or equipment (flexibility)	1	Yes
		2	No
10	EDI	1	Available
		2	Not available

This research postulates $Q = 10$ attributes (Table 2.2) to influence the trucking carrier choice. Attributes q are selected based on the literature review (Table 2.1 , and Randall et al., 2010). Levels ℓ_q are proposed based on a combination of literature review, and authors' experience/criteria. These are complemented with conversation to agents in the trucking market. Price ($q = 1$) and delivery time ($q = 2$) are the most evident attributes for any analysis of transportation services. ℓ_1 are based on the savings reported by Caplice and Sheffi (2006). ℓ_2 are based on the regular operation of shippers. Loss/damage is explicitly captured by the refund attribute ($q = 5$). ℓ_5 are based on the research by Randall et al. (2010). Flexibility is taken into account by the attribute $q = 9$. ℓ_9 are also based on Randall et al. (2010). Discrete levels are required to properly deal with the multidimensionality of flexible services (flexibility to capacity, equipment, additional features, etc.), which turns the use of continuous levels unmanageable for the experiment. Frequency is approximated by the regularity of the service ($q = 8$). Again ℓ_8 are discretized to encapsulate regular/irregular services and reduce design complexity. Fleet size and average model of trucks ($q = 3,4$) represent carrier specific values that provide reliability to the customer. ℓ_3 are based on the report by Transportation Topics (2011) and ℓ_4 on data by RITA (2013). Customer relationship is taken into account by the experience attribute ($q = 6$). ℓ_6 are based on the findings by Caplice and Sheffi (2006). Consolidation and value-added extensions are encapsulated by the type of

shipment attribute ($q = 7$). Finally, the impact of new technologies is captured by the EDI attribute ($q = 10$). ℓ_6 and ℓ_7 are based on the work by Randall et al. (2010).

The optimal experiment design approach proposed by Street and Burgess (2007) is used to determine an optimal number of cases \bar{N} . Each case with a unique combination of levels for each attribute. After analyzing and testing the design it is found to be too long for the current study. So, a heuristic technique is used to select a good-quality subset of $N < \bar{N}$ cases from the optimal design. This is a delicate task because it is easy to sample combinations of cases without sufficient variability for the levels of the attributes., e.g., a level appears most of the times in the sampled cases. To overcome this bias, a simulated annealing metaheuristic is implemented to search for samples that minimize the summation of variance associated to level counts. Details of this method are presented in Appendix A.

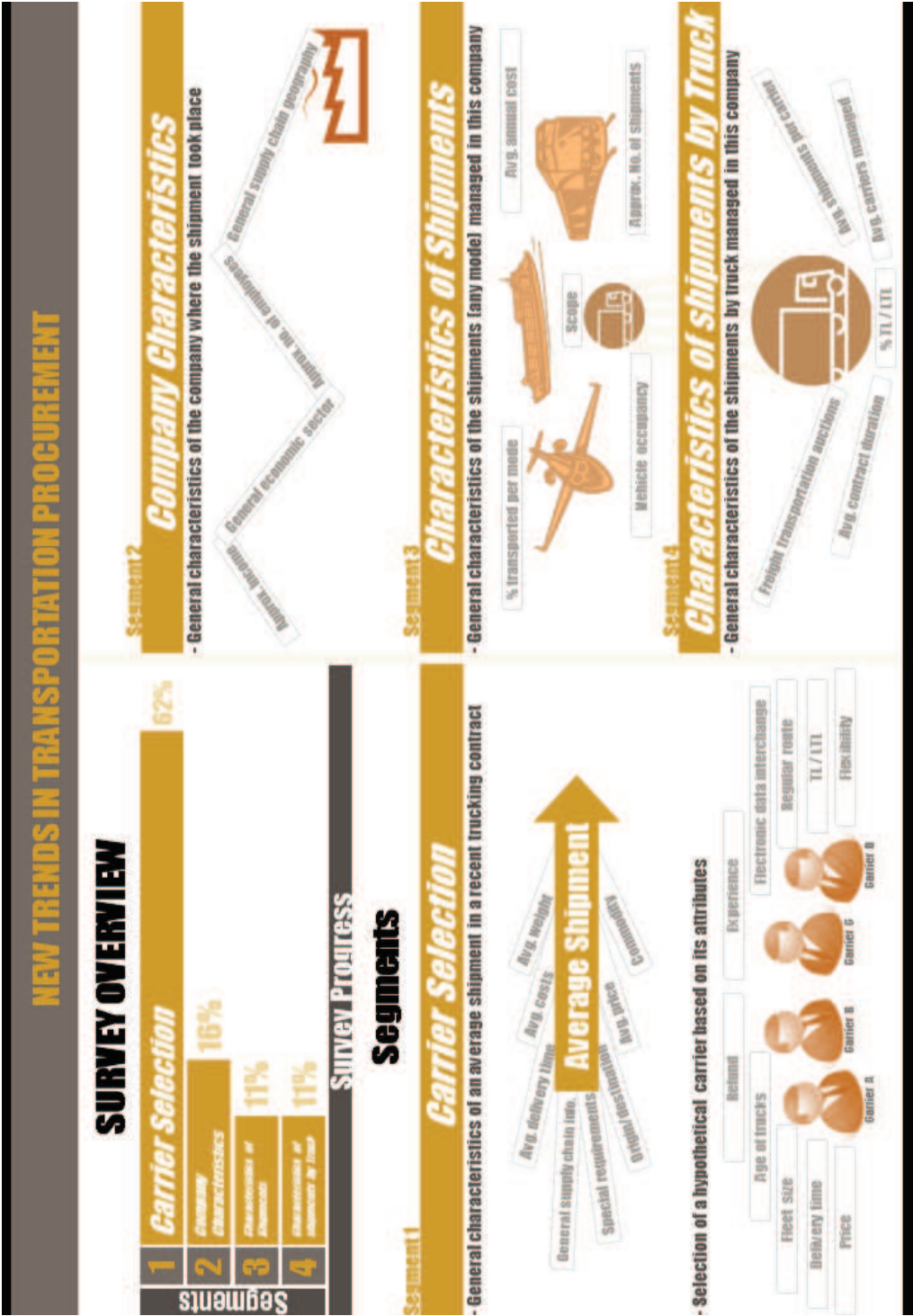


Figure 2.1 Infographic: survey overview and summary of collected data

Finally the experiment considers $N = 18$ cases and $M = 4$ hypothetical carriers. is an example of one of the cases presented to the shippers.

Table 2.3 Sample carrier selection choice set

Attribute	Carrier A	Carrier B	Carrier C	Carrier D
Price *	30% below	30% above	10% below	10% above
Delivery time *	Maximum	Average	Average	Minimum
Fleet Size (Power Units)	100	1,000	10,000	10,000
Average model of trucks	2001	2001	2012	2006
Refund if service not provided as agreed	50% price	50% price	110% price	80% price
Experience with the carrier	Unsatisfactory experience	No experience	Satisfactory experience	Satisfactory experience
Type of shipment	Direct (TL)	Direct (TL)	Consolidated (LTL)	Consolidated (LTL)
Service for this OD	Irregular/ Unusual	Irregular/ Unusual	Regular/ Usual	Regular/ Usual
Flexible to changes in capacity and or equipment	No	No	Yes	Yes
EDI	Available	Available	Not avail.	Not avail.

* These values are with respect to information previously provided
Choice-set context: "For the truck shipment that you just described, suppose that you have narrowed down your choice of carriers to the following 4 options. Please review the attributes of each carrier and select the one that you would choose."

An online survey is implemented in Qualtrics (ITaP, 2014) to present the SCE to respondents and collect additional data. Respondents are professionals with experience in the procurement of trucking services. The flow of the survey is shown in Figure 2.1. First, the respondent is asked to describe an average shipment in the most recent trucking contract and the SCE is presented based on it (Segment 1). The SCE shows 18 cases to the respondent. Levels are properly varied case after case. Table 2.3 is an example of one of them. For each case the responded is asked to select the most convenient carrier (trucking service) for the stated shipment. To reduce the error induced by respondents

waiting for carriers that exactly match their experiences, shippers are informed that these are the only four carriers available after narrowing down all the possibilities in the market. Then, general characteristics of the firm where this shipment took place are collected (Segment 2), followed by general characteristics of the shipments managed there (intermodal in Segment 3 and only truck in Segment 4). These are the shipment/shipper attributes that are not considered in these models by previous researchers. Additional information is available in the website developed for this survey (Mesa-Arango, Ukkusuri 2013). Professionals in all transportation areas were invited to respond to the survey via email using the large LexisNexis databases available at Purdue University. Likewise, the invitation was posted on selected Linked-In groups, a popular social network for professionals. About 300 people responded to the invitation but only 72 had the respondent profile and completed the survey. Respondent profile was strictly checked ensuring that only professionals with trucking procurement were surveyed. Notice that each respondent faces 18 hypothetical selection scenarios for a total of 1296 observations.

Table 2.4 presents summary statistics for selected variables of the shipments and shippers covered by the survey. The average shipment price is roughly \$1,400, 0.6% of the average shipment value (about \$250,000), and 5% of the inventory cost (about \$30,000). The average accepted delivery time is one week. The average minimum and maximum acceptable delivery times are 4 days and about 2 weeks respectively. On average, these shipments are associated to a volume of 4,000 shipments per month. 48% of the shipments in the dataset are related to a pull-only strategy, i.e., shipments are sent in direct response to customer orders (make to order). This shows the high effect that real-time demand information has in the new supply chains and how information

technologies are playing an important role in new business. About 44% combines push, i.e., shipments are sent in anticipation to orders (make to stock), with some level of pull strategy, showing that firms are combining hybrid supply chain models to optimize their distribution channels. Only 8% of the respondents managed pull-only shipments. Although 47% of the respondents represent large firms, there is sufficient representation of respondents from smaller firms.

Table 2.4 Summary statistics for selected variables of the shippers and shipments

Variables of shippers and shipment	Mean	Std. Dev	Min	Max
Shipment Price (\$)	1,435.9	1,939.2	9.8	15,000
Minimum accepted delivery time (day)	4.117	8.424	0.3	48
Average accepted delivery time (day)	7.358	12.680	1	48
Maximum accepted delivery time (day)	13.548	24.921	1	120
Shipment weight (ton)	14.519	9.929	0.0	45.0
Value of goods in shipment (\$)	250,867	1,750,910	100	15,000,000
Shipment inventory cost (\$)	29,749	175,423	0	1,500,000
Shipments per month (shipments/month)	3,974	14,064	1	100,000
Pull-only strategy (bin)	0.479	0.503	0	1
Firm yearly income less than \$25 Million (bin)	0.306	0.461	0	1
Firm yearly income between \$25 and \$100 Million (bin)	0.222	0.416	0	1
Firm yearly income greater than \$100 Million (bin)	0.472	0.499	0	1
(bin) Binary variable				

Although the sampled population has an acceptable level of representativeness, some aspects have to be considered when analyzing the results: Shippers paying high prices, with highly frequent shipments, and with heavy loads are underrepresented in the dataset.

Table 2.5 presents summary statistics for the attributes of the hypothetical carriers selected by respondents in the SCE. Notice that they provide general insights but specific conclusions can only be drawn from the model developed in Section 2.5. Likewise, these

summary statistics should be analyzed carefully from the context of the experiment itself. Again, this is not a problem for the results of the subsequent model. It is observed that shippers do not always select the cheapest option, this happens in 60% of the cases. There is a trend to select low-price options though, i.e., 40% and 38% of the selected services are priced 30% and 10% below the average price respectively. Still, 14% and 7% of the selected carriers correspond to services priced 10% and 30% above the average. These interesting results show that although shippers are looking for low-price options to reduce their transportation procurement costs, some of them are willing to select services with higher price to maintain certain attributes of the services in combination to characteristics of the shipments. This is also supported by the findings in the work by Caplice and Sheffi (2006).

Table 2.5 Summary statistics for attributes of the hypothetical carriers selected in the SCE

Attributes offered by carriers selected in the SCE*	Mean	Std.Dev
Price is 70% of the average shipment price	0.403	0.491
Price is 90% of the average shipment price	0.383	0.486
Price is 110% of the average shipment price	0.142	0.350
Price is 130% of the average shipment price	0.072	0.258
Delivery time is the average accepted	0.415	0.493
Delivery time is the minimum accepted	0.310	0.463
Delivery time is the maximum accepted	0.275	0.447
Fleet of 10000 trucks	0.457	0.498
Fleet of 1000 trucks	0.259	0.438
Fleet of 100 trucks	0.285	0.451
Fleet with 2001 as average make year	0.267	0.443
Fleet with 2006 as average make year	0.307	0.462
Fleet with 2012 as average make year	0.425	0.495
Refund is 50% if the service is not provided as agreed	0.301	0.459
Refund is 80% if the service is not provided as agreed	0.365	0.482
Refund is 110% if the service is not provided as agreed	0.334	0.472
No Previous experience with the carrier	0.357	0.479

Attributes offered by carriers selected in the SCE*	Mean	Std.Dev
Previous satisfactory experience with the carrier	0.499	0.500
Previous unsatisfactory experience with the carrier	0.144	0.351
LTL carrier	0.452	0.498
Irregular/Unusual service for this OD	0.467	0.499
Flexible to changes in capacity and/or equipment	0.510	0.500
EDI availability	0.565	0.496

* Indicator variables equal to one if the description of the attributes is satisfied, zero otherwise

Looking at the delivery times, in the majority of the cases (42%) shippers select services that correspond to the average accepted. The second largest segment corresponds to the minimum accepted delivery time (31% of the cases). Although some shippers prefer fast service, average times are more desirable because they are related to synchronized operations. Accelerated deliveries might involve additional inventory costs that reduce the value of the supply chain as a whole. On the other hand, the maximum accepted delivery time is selected in 27% of the cases. This is lower because long delivery times incur opportunity costs related to the risk of delaying the supply chain orchestration and hence losing future business when supplies are not delivered on time.

In many cases shippers prefer carriers with a large fleet and recent trucks (46% for carriers with 10,000 trucks and 42% for trucks where the average make year is 2012) because they are related to more reliable services when a large number of trucks is quickly available and newer vehicles have a reduce number of technical incidents on the roads.

As expected, shippers tend to select carriers with whom they had previous satisfactory experience (50% of the cases). Remarkably, they select new carriers in more cases than carriers with whom they had unsatisfactory experiences (36% versus 14%). This significant finding tells trucking carriers that quality of service is a very important

aspect in current business and customer satisfaction dramatically draws the line between keeping businesses and losing them to new carriers.

The analysis of the main types of trucking systems, i.e., truckload (TL) and LTL, shows that there is a slightly preference for the former (55% of the cases). This follows the market trends where TL has higher shares than LTL services. In the United States, it is estimated that TL accounts for 61% of the 2013 general trucking industry revenue \$193.4 Billion (Setar, 2013a, 2013b).

EDI allows exchanging documents between shippers and carriers via internet. This reduces the inconvenience of other channels, e.g., faxes, mails, or phone calls, and the transmission of errors by multiple manipulations of the documents. EDI simplifies the process of shipper service request, carrier response, shipment tracking, payment and invoice. In the new environment surrounded by advances in information technology, EDI is expected to be a competitive advantage for the carriers. In fact, the summary statistics shows that in 57% of the cases carriers with this service are preferred.

It is expected that shippers prefer carriers providing services over regular or familiar routes since this would increase the reliability of the service as carriers are aware of disruptions and general conditions of these routes. This is supported by the general statistics where these carriers are selected in 53% of the cases. However, the number of choices for the opposite carriers (serving unfamiliar or irregular routes) is very similar (47%) indicating that there are other attributes that might have higher relevance. Likewise, the general statistics indicate that in 51% of the cases shippers prefer carriers with flexibility to changes in capacity and/or equipment. This is expected because this reduces the risk of not having the right truck if demand and businesses fluctuate. Again,

the number of choices for not-flexible carriers is similar (49%). Finally, there is no clear trend with respect to the attribute for service refund. This will be analyzed in Section 2.5.

The following subsection describes the econometric approach followed to understand carrier selection and shipper WTP.

2.4 Econometric approach

In the experiment described before each shipper is asked to consider a set of hypothetical cases and each case is a choice set of hypothetical carriers. Since the responses for each shipper share independent unobserved effects, they constitute a panel of data. The methodology below follows the work by Train (2009) with respect to mixed logit models for panel data.

Discrete choice models offer an econometric framework suitable to model the selection of trucking carriers. The multinomial logit (MNL) model is widely used for this purpose. However, the MNL neither allows considering random taste variation nor correlation of unobserved factors, and it has restrictive substitution patterns. These limitations are overcome by the mixed logit model. The utility U_{njt} of selecting alternative i in the hypothetical case n by shipper t is presented in Equation (2.1), where X_{njt} is a vector of variables, β is a vector of estimated parameters, and ε_{njt} is a random term (iid extreme value).

$$U_{njt} = \beta' X_{njt} + \varepsilon_{njt} \quad (2.1)$$

For panel data and since ε_{njt} are independent among shippers, the probability $L_{ni}(\beta)$ of selecting alternative i in case n conditional on β is given in Equation (2.2), where T is the total number of panels, i.e., shippers.

$$L_{ni}(\beta) = \prod_{t=1}^T \frac{e^{\beta' x_{nit}}}{\sum_j e^{\beta' x_{njt}}} \quad (2.2)$$

The unconditional probability P_{ni} (Equation (2.3)) is the integral of the product in Equation (2.2) over all values of β . Here $f(\beta)$ is the continuous density function of β . Notice that $f(\beta)$ can follow any distribution, e.g., normal, lognormal, uniform, triangular, gamma, etc. Thus, the estimation of the model requires finding the distribution and structural coefficients of $f(\beta)$, e.g., for the normal distribution $f(\beta) = \phi(\beta|\mu, \sigma)$ estimated coefficients are: mean μ and standard deviation σ .

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \quad (2.3)$$

The estimation of the mixed logit model for panel data is similar to the estimation of the regular mixed logit. $L_{ni}(\beta)$ is computed by generating draws of β from $f(\beta)$. This process is repeated for a sufficient number of draws and the results are averaged to obtain a simulated P_{ni} that is used to compute the likelihood function, which is maximized to estimate β . As shown by Bhat (2003) and Train (1999), Halton draws are more efficient than purely random draws. More details about simulation-based maximum likelihood methods are found in the following works: Boersch-Supan and Hajivassiliou (1993), Brownstone and Train (1999), Geweke et al. (1994), McFadden and Ruud (1994), and Stern (1997).

After a model is estimated, the corresponding marginal effect $ME_{x_{nit}}^{P_i}$ that describes how unitary changes in variable x_{nit} affect the outcome probability P_i is estimated using Equation (2.4).

$$ME_{x_{nit}}^{P_i} = \frac{\delta P_i}{\delta x_{nit}} \quad (2.4)$$

Furthermore, marginal rates of substitution can be computed as presented in Equation (2.5) to determine the relative magnitude of any two parameters β_{ia} and β_{ib} estimated in the model. When β_{ib} correspond to the parameter estimated for the price, the estimated *MRS* indicates the WTP for a unitary change in the attribute related to β_{ia} .

$$MRS(i)_{ba} = \frac{\beta_{ia}}{\beta_{ib}} \quad (2.5)$$

The next section presents and discusses the results of the mixed logit model, marginal effects and shipper WTP.

2.5 Estimation Results

This section presents the results of the estimated mixed logit model for trucking service carrier selection. Then, the marginal effects and shipper WTP for attributes of the services are computed.

After several iterations, the mixed logit model that represents the best specification for truck service selection is presented in Table 2.6. The software used for model estimation is LIMDEP 9 (NLOGIT 4). Variables in the model are significant and have intuitive signs. Random parameters follow a normal distribution. The mean is presented over the standard deviation (in parenthesis).

Table 2.6 Mixed logit model for carrier selection

Variable	Parameter	t-stat
Fixed parameters		
Service Price (\$)	-1.612×10^{-3}	-13.76
Delivery time offered by the carrier * shipment weight (day * ton)	-4.931×10^{-3}	-2.861
Shipment value * {LTL carrier} (\$)	-1.063×10^{-5}	-2.769
Shipment inventory cost * {Carrier serves irregular/unusual route} (\$)	-1.103×10^{-5}	-2.743
{Some-level-of-push shipment} * {Flexible carrier} (bin)	4.924×10^{-1}	3.88
{Low-income shipper} * {Satisfactory experience with carrier} (bin)	1.121	7.189
{High-income shipper} * {Satisfactory experience with carrier} (bin)	6.441×10^{-1}	6.518
{Low-income shipper} * {Unsatisfactory experience with carrier} (bin)	-6.817×10^{-1}	-3.465
{High-income shipper} * {Unsatisfactory experience with carrier} (bin)	-1.459	-10.392
{Carrier with EDI availability} (bin)	4.820×10^{-1}	5.497
{High-income shipper} * Carrier fleet size (trucks)	2.336×10^{-5}	2.286
Refund if service is not provided as expected (\$)	4.088×10^{-4}	4.033
{Carrier offers maximum accepted delivery time} (bin)	-1.206×10^{-1}	-1.275
Random parameters		
Ln(Number of similar shipments per month)* {LTL carrier}	-7.507×10^{-5}	-0.941
(shipments/month)	(5.446×10^{-1})	7.484
Current year – Average make model of carrier's fleet (years)	-4.084×10^{-2}	-4.272
	(3.545×10^{-2})	3.289
1296 Observations		
Log likelihood at convergence = -1329.277		
Log likelihood at zero = -1796.63		
$\rho^2 = 0.26013$		
Adjusted $\rho^2 = 0.25650$		
Random parameters are associated to a normal distribution and estimated with 400 Halton draws		
(Standard deviations in parenthesis)		
{A} is an indicator function equal to 1 if condition A is satisfied, zero otherwise		
(bin) Binary variable		

The likelihood ratio is used to test the overall significance of the mixed logit model, i.e., unrestricted model U (Table 2.6), over the corresponding MNL, i.e., restricted model R . The likelihood ratio test statistic is presented in Equation (2.6), where $LL(\beta_R) = -1420.722$ is the log-likelihood at convergence of the corresponding MNL, and $LL(\beta_U) = -1329.277$ is the log-likelihood at convergence of the mixed logit Model.

$$\chi^2 = -2[LL(\beta_R) - LL(\beta_U)] \quad (2.6)$$

$$\begin{aligned}
U_i = & -(1.612 \times 10^{-3})x_i^p - (4.931 \times 10^{-3})x_i^t y_{ton} - (1.063 \times 10^{-5})x_i^{LTL} y_{val} \\
& - (1.103 \times 10^{-5})x_i^{irte} y_{inv} + (4.924 \times 10^{-1})x_i^{flex} y_{push} \\
& + (1.121)x_i^{sat} y_{linc} + (6.441 \times 10^{-1})x_i^{sat} y_{hinc} \\
& - (6.817 \times 10^{-1})x_i^{unsat} y_{linc} - (1.459)x_i^{unsat} y_{hinc} \\
& + (4.820 \times 10^{-1})x_i^{EDI} + (2.336 \times 10^{-5})x_i^{fleet} y_{hinc} \\
& + (4.088 \times 10^{-4})x_i^{ref} - (1.206 \times 10^{-1})x_i^{maxt} \\
& + [-7.507 \times 10^{-5}, 5.446 \times 10^{-1}]x_i^{LTL} \ln(y_{shmts}) \\
& + [-4.084 \times 10^{-2}, 5.446 \times 10^{-1}]x_i^{age}
\end{aligned} \tag{2.7}$$

The chi-squared $\chi^2 = 182.89$ is distributed with two degrees of freedom (two more parameters estimated in the mixed logit model, i.e., standard deviations of random parameters). The right-tailed probability of this χ^2 distribution is 2×10^{-40} . Thus, using a 98.5% level of confidence, the MNL can be rejected and the mixed logit is preferred.

Equation (2.7) presents the econometric specification of the model in Table 2.6, where U_i is the utility of selecting the trucking service i . Variables related to the alternative i are: the service price x_i^p (\$), delivery time x_i^t (days), fleet size for the carrier x_i^{fleet} (trucks), refund offered if i is not provided as agreed x_i^{ref} , average age of carrier's fleet $x_i^{age} = \text{current year} - \text{average make model of carrier's fleet (years)}$, and binary indicator variables $x_i^{LTL} = 1$ if i is LTL, $x_i^{irte} = 1$ if i is a regular origin-destination (OD) served by the carrier, $x_i^{flex} = 1$ if the carrier is flexible to changes in capacity and/or equipment, $x_i^{sat} = 1$ if the shipper has satisfactory experience with the carrier, $x_i^{unsat} = 1$ if the shipper has unsatisfactory experience with the carrier, $x_i^{EDI} = 1$ if the carrier has EDI availability, $x_i^{maxt} = 1$ if delivery time is associated to the maximum time accepted

by the shipper, $x_i^{LTL} = x_i^{irte} = x_i^{flex} = x_i^{sat} x_i^{unsat} = x_i^{EDI} = x_i^{maxt} = 0$ otherwise (respectively). On the other hand, variables related to the decision maker (shipper) are: shipment size y_{ton} (ton), shipment value y_{val} (\$), shipment inventory cost y_{inv} (\$), shipments per month in this contract y_{shmts} (Shipments/month), and binary indicator variables $y_{push} = 1$ if the shipper has some level of push supply-chain strategy, $y_{linc} = 1$ if shippers annual income is less than \$50 million, $y_{hinc} = 1$ if shipper annual income is more than \$50 million. Notice that there is no loss of generality by using y_{linc} and y_{hinc} together for model estimation because it is an unlabeled experiment and these attributes are properly interacted with attributes of the alternatives. Notation $[\mu, \sigma]x$ indicates that variable x is associated to a random parameter that is normally distributed with mean μ and standard deviation σ .

Table 2.7 Marginal effects and WTP for attributes in the mixed logit model for carrier selection

Variable	<i>ME</i>	<i>MRS</i>	
		WTP ↓ [\$]	WTP ↑ [\$]
Fixed parameters			
Service Price (\$)	-0.214 (0.217)	--	--
Refund if service is not provided as expected (\$)	0.046 (0.055)	--	0.254
{Carrier with EDI availability} (bin)	0.0300 (0.035)	--	298.922
{High-income shipper} * {Unsatisfactory experience with carrier} (bin)	-0.025 (0.053)	904.667	--
Shipment value * {LTL carrier} (\$)	-0.023 (0.047)	0.007	--
{High-income shipper} * {Satisfactory experience with carrier} (bin)	0.022 (0.042)	--	399.498
{Low-income shipper} * {Satisfactory experience with carrier} (bin)	0.016 (0.053)	--	695.524
Shipment inventory cost * {Carrier serves irregular/unusual route} (\$)	-0.016 (0.183)	0.007	--
Delivery time offered by the carrier * shipment weight (day * ton)	-0.016 (0.045)	3.058	--
{Some-level-of-push shipment} * {Flexible carrier} (bin)	0.015 (0.031)	--	305.412

Variable	<i>ME</i>	<i>MRS</i>	
		WTP ↓ [\$]	WTP ↑ [\$]
{High-income shipper} * Carrier fleet size (trucks)	0.008 (0.014)	--	0.014
{Low-income shipper} * {Unsatisfactory experience with carrier} (bin)	-0.006 (0.021)	422.784	--
{Carrier offers maximum accepted delivery time} (bin)	-0.004 (0.007)	74.809	--
Random parameters			
Ln(Number of similar shipments per month)* {LTL carrier} (shipments/month)	0.057 (0.096)	722.154*	629.027**
Current year – Average make model of carrier's fleet (year)	-0.029 (0.026)	69.298*	18.643**
Random parameters associated to a normal distribution (Standard deviations in parenthesis) {A} is an indicator function equal to 1 if condition A is satisfied, zero otherwise bin: Binary variable * Two standard deviations below the mean ** Two standard deviations above the mean * and ** Cover 95% of the observations WTP ↓ Indicates the shipper WTP for an unitary reduction in the corresponding variable WTP ↑ Indicates the shipper WTP for an unitary increment in the corresponding variable (bin) Binary variable			

Table 2.7 presents the corresponding marginal effects *ME*, used to quantify the effect that a unitary change in a variable of the model has in the carrier selection probability, and marginal rates of substitution *MRS*, to quantify the shipper WTP for these attributes. Variables in this table are sorted in descending order with respect to absolute value of the *ME*. So, variables in the top have higher impact in the carrier selection probability than variables in the bottom. Fixed and random parameters are also differentiated.

Results are similar to previous research for different freight contexts, where high price reduces the probability of a freight choice (Anderson et al. 2009, Brooks et al. 2012, Cavalcante and Roorda 2013, Danielis and Marcucci, 2007, Fries et al. 2010, Masiero and Hensher, 2010, 2011, and 2012, Patterson et al. 2010, Pucket et al. 2011, Train and Wilson, 2008), increased delivery time reduces the attractiveness of a freight alternative (Anderson et al. 2009, Brooks et al. 2012, Danielis and Marcucci, 2007, Masiero and

Hensher, 2010, 2011, and 2012, Fries et al. 2010, Train and Wilson, 2008), heavy weighted shipments prefer options with shorter deliveries (Masiero and Hensher, 2012), reliable freight alternatives are more likely to be selected (Brooks et al. 2012, Cavalcante and Roorda 2013, Danielis and Marcucci 2007, Fries et al. 2010, Masiero and Hensher, 2010, 2011, and 2012, Patterson et al. 2010, Train and Wilson, 2008), damage risk decreases the probability of selecting a freight choice (Cavalcante and Roorda 2013, Danielis and Marcucci, 2007, Masiero and Hensher 2012, Patterson et al. 2010), intermodal services -similar to LTL in this context- overall reduces selection probability (Patterson et al. 2010), and flexible freight services are more likely to be selected (Danielis and Marcucci, 2007). In the following analysis, variables are classified in five groups related to price and time, reliability, experience with the carrier, and carrier-specific characteristics.

2.5.1 Price and time

The first group of variables is service price and time, indispensable for any transportation analysis. Price is the main attribute driving the choice of carriers and has a negative effect on its selection probability. So, as the price offered by a carrier increases the probability of selecting it decreases. From the marginal effects computed in Table 2.7 it is observed that \$1 increment in price, on average reduces the probability of selecting a carrier by 21.4%. Intuitively, given a set of homogeneous trucking carriers and services, the one offering the lowest price has the highest probability of being selected. However, as carriers show more heterogeneous features and services, probabilities change and the cheapest will not be the most desired one.

The temporal dimension is captured by the product between delivery time offered by the carrier and the shipment weight. This variable has a negative effect in the carrier selection probability. A unitary change in this product on average decreases the probability of selecting a carrier by 1.6%. So for a fixed shipment, carriers offering faster deliveries are preferred. Notice that the weight incorporates characteristics of the shipment that are useful when analyzing different types of business. Furthermore, on average a shipper would pay \$3 per ton for each day of delivery time saved. Notice that small shipments require higher time savings than large shipments to take full advantage of this, e.g., the shipper WTP for a day saved by 1-ton shipment is equivalent to half day saved for 2 ton. Following this idea, carriers offering the maximum delivery time are less desirable. This is supported by the negative sign of the corresponding parameter in the model. On average, carriers offering this time decrease their selection probability by 0.4%. Shippers are willing to pay \$75 for services where the delivery time is lower than the maximum accepted. There is potential opportunity cost related to the maximum accepted delivery time. If shipments are delayed above the maximum delivery threshold the supply chain processes are potentially delayed and there is risk for perishable products to get damaged. This affects the image of the agent coordinating transportation and increases the likelihood of losing future businesses. So, although shippers would perceive lower prices for these carriers, they must be aware of these risks when selecting them. On the other hand, carriers should prefer to providing services with delivery times that do not approximate to the maximum accepted by the shipper.

2.5.2 Reliability

The second group of variables is related to reliability. Variables related to service refund and route irregularity are used as proxies of reliability in order to provide transferable insights and avoid subjectivities related to this concept. Carriers offering refund if the service is not provided as expected are more likely to be selected. The positive sign in the model indicates that the probability of being selected increases as the amount refunded increases. On average \$1 refunded increases the selection probability by 4.6% and shippers are willing to pay \$0.25 for every dollar offered in refund. Shippers want reliable services and they would pay more to carriers offering refunds. These are good news for carriers with reliable and very predictable services because they can increase their revenues by offering high refunds, and, hence, high prices. Randall, et al. (2010) found that some carriers are offering refunds greater than or equal to the service price. However, this strategy is risky for carriers and services where there is a high probability of providing a low level of service, e.g., unfamiliar routes, unpredictable weather or traffic, low capacity or flexibility, among others. Carriers with these conditions should be cautious using high refunds as a justification for increased prices.

Shippers do not favor carriers serving routes that are irregular or unusual for them. The probability of selecting a carrier decreases proportionally to the amount of inventory cost associated to the shipments. This is supported by the negative sign of the parameter for the corresponding variable in the model. On average, \$1 increment in inventory cost reduces the selection probability of these carriers by 1.6%. Shippers would pay on average 0.7 cents for every dollar of inventory cost in order to avoid carriers with these characteristics. This highlights the importance of reliability for shippers, who are willing

to pay more in order to avoid carriers that are not familiar with the route between the OD of the shipment. These carriers have few experience with the condition of this route and are likely to pickup or deliver shipments at undesired times. This translates into additional inventory costs when shipments are delayed. Shippers can use this important result to benchmark prices as suggested for other variables above. Carriers can benefit because they can price higher for services related to familiar routes and increase the price for shipments with high inventory costs.

2.5.3 Experience

The third group of variables captures the effect that experience with the carriers has in its selection probability for future contracts. Unsatisfactory experience with the carrier is not desired by the shippers. However, it is more undesirable for high-income shippers, i.e., yearly income greater \$20 million. This is supported by the negative sign of the parameters related to these variables. On average, unsatisfactory experience with the carrier decreases its selection probability by 2.5% for high-income shippers and 0.6% for low-income shippers (yearly income less than \$20 million). Thus, high-income shippers are willing to pay \$905 more for new carriers or carriers that do not represent unsatisfactory experience. Low-income shippers would pay \$423 instead (53% less). In contrast, the positive parameter associated to the variables for satisfactory experience with the carrier show that, on average, their selection probability increases by 2.2% for high-income shippers, and 1.6% for low-income shippers. High-income shippers would pay \$399 and low-income carriers would pay \$695 for this feature. Interestingly, for high-income shippers the WTP to avoid a carrier with unsatisfactory experience is higher than the WTP to maintain a carrier with satisfactory experience. The opposite happens for

low-income shippers, i.e., the WTP to avoid a carrier with unsatisfactory experience is less than the WTP to maintain a carrier with satisfactory experience. So, low-income shippers are more familiar with unsatisfactory experiences and highly value carriers with high standards. This information can be used by shipper in a negotiation process, e.g., if a carrier with unsatisfactory experience offers low prices to a shipper she can take this as a benchmarking price to negotiate with other carriers. Experience is private information of the shipper, so other carriers would be pressured to reduce their prices to compete with the benchmarking price. Again, there is a risk if the benchmarking price is associated to a carrier with a negative reputation because other carriers would not take it as a serious competitor. In this example, economies would be higher for high-income shippers. It is easy to set a similar negotiation example for a carrier with satisfactory experience. On the other hand, carriers planning new business or carriers maintaining good level of service with shippers can use this information to price higher for their services. Although for new business carriers can price higher to low-income shipper than high-income shippers, they can expect higher revenues (related to high prices) if they maintain satisfactory experiences with high-income shippers.

2.5.4 Carrier-specific characteristics

The last set of variables aggregates features specific to the services provided by the carrier, i.e., EDI, consolidation (LTL), flexibility, fleet size, fleet age. Two of the variables in this group are related to random parameters. Shippers prefer carriers that provide EDI in their services, as supported by the positive sign in the model. On average, a service with EDI availability increases the carrier selection probability by 3.0%. The average WTP for this feature is \$299. EDI represents benefits for both shippers and

carriers because they correct billing errors and exchange information and money in real time. This is important for shippers because they can easily systematize and synchronize their supply chains. New technologies are penetrating all economic sectors and trucking cannot be the exception. This important finding tells carriers that they can incorporate EDI into their business and, in turn, price higher for this feature, which covers investment cost and provides additional future revenues.

Consolidated services (LTL carriers) are less preferred than direct services (TL carriers). The probability of selecting an LTL carrier decreases proportionally to the value of the shipment. This is supported by the negative sign of the parameter for this variable. On average, \$1 increment in shipment value decreases the probability of selecting an LTL carrier by 2.3%. A shipper would pay 0.7 cents less for every \$1 of shipment value for a consolidated service than a direct one. The high level of manipulation for LTL shipments increases its damage risk. Hence, this result is similar to other research where damage risk decreases the selection probability of a specific freight choice. Naturally, damage is more relevant for expensive shipments. Shippers expect LTL services to be cheaper than TL. So, they can benchmark saving opportunities by comparing TL and LTL prices, the closer they are the higher the savings they obtain by selecting TL, especially for high-value shipments. From the carrier perspective this indicates that LTL carriers potentially charge lower than TL but they are very competitive for low-value shipments.

Shippers with shipments associated to some level of push strategy prefer carriers that are flexible to changes in capacity and/or equipment. This is supported by the positive parameter of the corresponding variable in the model. On average for these shipments,

the probability of selecting a carrier increases by 1.5% if it is flexible. In this case, shippers would pay \$305 for this feature. Pure push strategy is related to planned, ideally regular, and predictable shipments. However, these ideal conditions are not the standard in freight markets driven by demand uncertainty, seasonality effects, network disruptions, irregular macroeconomics and market conditions. Thus, shippers adjust the operation of their supply chains by adding some levels of pull strategy, i.e., there is some level of regularity on shipments but they also adjust to variant conditions. This new trend in supply chain management justifies the selection of flexible carriers. Additionally, if carriers want to be competitive in the new economic environment, they have to provide flexibility in their services. Although this is easier for large trucking companies, it is challenging for small carriers who should consider cooperation strategies (with other carriers), or joining the pool of carriers available to third-party logistics (3PL) companies that agglomerate small trucking firms in order to be more competitive.

High-income shippers, i.e., yearly income greater \$25 million, increase the probability of selecting a carrier proportionally to its fleet size. This is supported by the positive sign of the parameter for this variable in the mixed logit model. On average, an additional truck increases the carrier selection probability by 0.8% for high-income shippers. These shippers would pay 1.4 cents for each additional truck. This could be also a proxy of reliability perceived by shippers. High-income shippers are less myopic to prices and compensate capacity availability (larger fleet) with higher prices. This is important for high-income shippers to benchmark savings when negotiating services with carriers that have different fleet sizes. Truckers benefit because they can justify fleet increments with price increments.

Heterogeneous tastes are observed by the shippers when selecting consolidated (LTL) services. This is supported by the random parameter associated to the indicator variable equal to the natural logarithm of the number of shipments per month if the carrier is LTL and zero otherwise. Such variability is associated to unobserved heterogeneity among respondents, an important feature of the underlying mixed logit model used to understand shipper behavior. For 44.5% of the shippers the probability of selecting LTL increases with respect to the number of shipments per month and for 55.5% of them it decreases. Therefore, the shipper WTP has mixed values. 95% of the observations are in the range between paying \$722 per unitary increment of this variable to avoid LTL carriers to paying \$629 per unitary increment to have them. Some reasons for the unobserved heterogeneity are captivity, few or no experience with a type of carrier, multiplicity of contractual agreements, business constraints, among others. This is an interesting motivation for future research extensions aiming to understand attributes that are relevant in the selection of consolidated (LTL) services.

For the majority of shippers (86%), the probability of selecting a carrier decreases as the average age of its trucks increases. However, the opposite happens for a low segment of shippers (12.4%), i.e., probability decreases as age decreases. This is evidenced by the random parameter for age-of-trucks estimated in the model. Similar to the previous case, this special capability of the mixed logit model allows the consideration of mixed tastes and unobserved heterogeneity. On average, shippers would pay \$27 for a year reduction in the age of the fleet. However, for 95% of the cases this value ranges from paying \$69 per year reduction to \$18 per year increment. So, carriers can benefit at a large extent by having newer trucks in the sense that they can price higher for their services as compared

to old-fleet carriers. However, they must be aware that some shippers would expect lower prices for newer trucks, because the efficiency of recent fleets reduces the operational costs of the carriers, and shipper would expect this savings to be reflected in their prices. This knowledge is relevant for shippers in a procurement process because they have arguments to negotiate prices for recent fleets from the efficiency perspective.

The estimated parameters, ME , and WTP provide general insights of the interaction between shippers and carriers. Furthermore, the model estimated in this Chapter can be used by shippers to rank carriers over a set of candidates for a transportation contract. The next section provides a numerical example to illustrate its application.

2.6 Numerical example

A numerical example is presented to illustrate the application of the mixed logit model and its importance for shippers and carriers. Consider a company (shipper) with \$50 million average yearly income ($y_{hinc} = 1$). A professional in charge of transportation procurement for this company is seeking carriers for a shipment with the characteristics presented in Table 2.8.

Table 2.8 Numerical example: shipment attributes

Shipment characteristics	Value
Maximum accepted delivery time (days)	8
Shipment weight y_{ton} (tons)	15
Value of goods in shipment y_{val} (\$)	250K
Shipment inventory cost y_{inv} (\$)	30K
Shipments per month y_{shmts} (Shipments/month)	4K
Supply change strategy y_{push} (binary)	Pull-only
K: Thousand	

After a comprehensive search, the professional narrows down the procurement possibilities to four candidate carriers (I, II, III, and IV) with the attributes summarized in Table 2.9.

$$P_i = \frac{e^{U_i}}{\sum_{j \in \{I, II, III, IV\}} e^{U_j}} \quad (2.8)$$

Equation (2.7) defines the average utility function U_i associated to carrier $i \in \{I, II, III, IV\}$. Utility functions are estimated through Monte Carlo simulation. For each iteration, random parameters are sampled from the corresponding distribution and the probability P_i of selecting carrier i is determined by the logit formula in Equation (2.8). Probabilities are computed for 1,000 iterations.

Table 2.9 Numerical example: attributes of the carriers

Attribute	Carrier			
	$i = I$	$i = II$	$i = III$	$i = IV$
Price x_i^p (\$)	1K	1K	750	750
Delivery time x_i^t (days)	7	8	5	6
Fleet Size x_i^{fleet} (truck)	120K	85K	50K	110K
Current year – Average make model of carrier's fleet x_i^{age} (years)	3	1	2	5
Refund if service not provided as agreed x_i^{ref} (\$)	400	0	1.1K	700
Satisfactory x_i^{sat} or unsatisfactory x_i^{unsat} experience with the carrier: (binary)	Unsatisf.	Satisf.	Satisf.	None
Type of shipment x_i^{LTL} (binary)	TL	TL* LTL**	TL* LTL**	TL
Service for this OD x_i^{irte} (binary)	Regular	Irregular	Regular	Irregular
Flexible to changes in capacity and/or equipment x_i^{flex} (binary)	Yes	No	No	Yes
EDI availability x_i^{EDI} (binary)	Available	Not available	Available	Not available

* First scenario, Figure 2.2(a)

** Second scenario, Figure 2.2(b), (c), and (d)

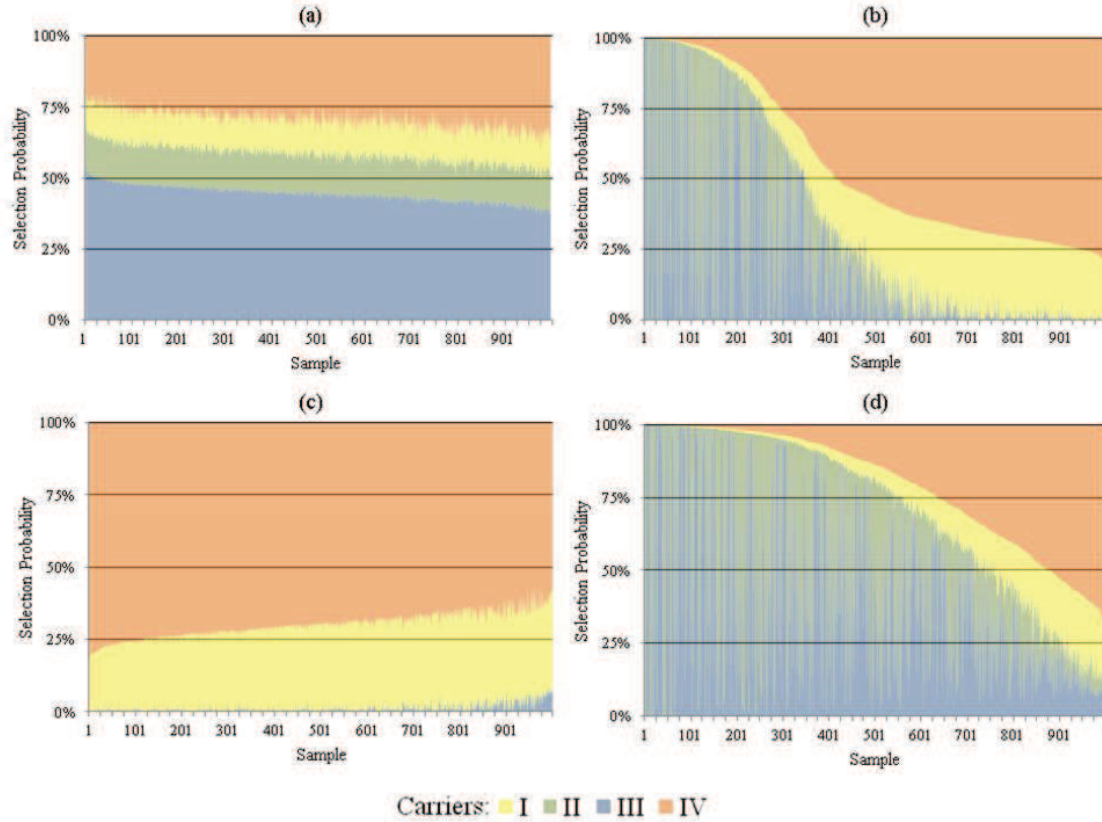


Figure 2.2 Simulated probabilities for (a) 4 TL carriers, 2 TL (I and IV) and 2 LTL carriers (II and III) with (b) unrestricted, (c) negative, and (d) positive random parameter sign.

In the first scenario all carriers offer consolidated services (TL). On average the selection probabilities are 11.6% for carrier I, 14.1% for carrier II, 44.4% for carrier III, and 29.8% for carrier VI. High preference for carriers III and IV is attributed to the combination of low prices with fast delivery times. Although carrier III has a small fleet, it is a slightly better option because of its higher refund, lower fleet age, satisfactory previous experience, regular service for this OD, and EDI availability. On the other hand carriers II and I are less desirable because they offer higher prices, slower delivery times, and low refunds. Notice that the effect of these attributes is not sufficient to compensate other positive features like large and recent fleets, satisfactory experience (carrier II),

regular OD service and EDI availability (carrier I). Furthermore, carrier I is highly penalized because of its unsatisfactory experience with the shipper. The simulated probabilities for this scenario are presented in Figure 2.2(a).

In the second scenario carriers II and III are assumed to offer consolidated (LTL) services. Other attributes remain the same. On average the selection probabilities are 18.0% for carrier I, 14.6% for carrier II, 21.7% for carrier III, and 45.6% for carrier IV. This is because on average LTL carriers are less desirable than TL and this low desirability is reinforced by the high shipment value and number of shipments per month considered in this example. Carrier III –who was the most attractive in the first scenario– is replaced by carrier IV –with similar features but consolidated shipments– and has a selection probability similar to the one for carrier I –least desirable in the first scenario–. Carrier II falls to the last position. However, from the simulated probabilities computed for this scenario (Figure 2.2(b)) it is observed that in few cases LTL carriers have a high chance of being selected over TL carriers while in others they are not considered at all. This is the result of unobserved heterogeneity captured by the random parameter.

Notice that some shippers have preferences towards TL or LTL carriers. So, they can use the random parameter as a fine tuning coefficient by weighting its sampled values. This idea is illustrated with the following examples. First, assume a shipper with low desirability for LTL carriers. This shipper can sample only negative values from the normal distribution of the LTL-related random parameter and analyze the results under this condition. This technique is applied to the previous example and the resulting simulated probabilities are reported in Figure 2.2(c). Here the average selection probabilities are 28.4% for carrier I, 0.3% for carrier II, 1.1% for carrier III, and 70.1%

for carrier IV. Evidently there is a preference for TL carriers and carrier IV is the most desired one. Second, a shipper with high tendency to LTL carriers can sample only positive values for the LTL-related random parameters. The resulting simulated probabilities from this technique are presented in Figure 2.2(d). In this case the average selection probabilities are 8.0% for carrier I, 27.9% for carrier II, 43.6% for carrier III, and 20.5% for carrier IV. Although there is a remarkable preference for LTL carriers, still TL has a significant chance to be selected. In this scenario carrier III takes back the first position mainly because of its initial attractive features and those added by the preference of the shipper towards LTL carriers.

This numerical example shows the flexibility of the model for shippers. Additional uses include employing alternative specific constants that weight decisions towards labeled choices. Nonetheless, these constants should be properly calibrated combining revealed preferences, adjusting labeled utilities and rescaling price and feature utilities (Ben-Akiva et al. 1994, Brownstone et al. 2000, Gilbride et al. 2008). The following section summarizes the work and findings of this research. Likewise, presents limitations and future research directions.

2.7 Conclusions

This Chapter investigates the selection of carriers for trucking services and the corresponding shipper WTP. A SCE is designed to collect data from shippers in one of the toughest fields for transportation surveys: freight. A set of variables are postulated to describe features of the trucking services offered by carriers. A discrete choice mixed logit model is estimated to determine the variables that are relevant in this process. The estimation of random parameters in this model allows the consideration of mixed tastes

among respondents and unobserved heterogeneity. Several variables of the shipper, shipment, and carrier, are found to be significant in this choice. Marginal effects are used to rank the importance of attributes with respect to the carrier selection probability. Marginal rates of substitution are used to estimate the shipper WTP. A detailed discussion of findings is provided to advise shippers and carriers in the negotiation of trucking services. A numerical example is presented to illustrate the application of the model.

The results herein are of significant importance with respect to transportation, logistics and supply chain management. The contributions of the Chapter are fourfold: (1) studying service choice by shippers that require trucking services, (2) postulating pragmatic attributes explaining this decision, (3) quantifying the corresponding WTP, and (4) providing meaningful negotiation guidance for shippers and carriers.

Shippers can use the results from this model to guide the negotiation of trucking services. They can compare prices with respect to tangible and implied features of themselves and the services offered by the carriers. Carriers can use these results to develop segmented pricing strategies that vary according to their characteristics, features of their services, characteristics of the shipper, and characteristics of other carriers competing for contracts. Table 2.10 summarizes key elements of the services preferred by shippers and pricing strategies for carriers, an incremental contribution to literature on transportation and logistics.

These insights are important for transportation researchers and policy makers in the sense that providing reliable, resilient, and efficient transportation networks can potentially affect the bottom line of business between shippers and carriers.

Table 2.10 Key elements for shippers and carriers regarding trucking-services and prices

Services preferred by shippers	Trucking-service pricing by carriers
Price and time	
Low price services but willing to pay additionally for valuable features.	Do not be afraid to price higher than other carriers if the service increases value for the shipper.
Short delivery times (heavy shipments value it more than light ones).	Price higher for services with reduced delivery times. Heavy shipments would pay more for time savings than light ones.
Delivery times that are not the maximum accepted by the shipper.	Price lower if the company can only guarantee the maximum expected delivery time.
Reliability	
Large refunds if services are not provided as expected.	Increase price proportionally to the refund offered if service is not provided as expected (consider failure risk and be cautious).
Carriers serving regular routes (especially for shipments with high inventory costs).	Price higher in regular routes and lower in irregular ones.
Experience	
Good experience with the carrier is better than no experience (more pronounced for small shippers).	Always provide services that are satisfactory for the shipper because this allows higher prices for future contracts.
No experience with the carrier is better than unsatisfactory experience (more pronounced for large shippers)	In the case of unsatisfactory experiences, prices have to be lower for future contracts.
Carrier-specific characteristics	
EDI availability.	Price higher if the company offers EDI.
Direct services (TL carriers).*	Price higher for direct services (TL carriers).*
Flexibility to changes in capacity or equipment (shipments with some level of push strategy).	Price higher if the company guarantees flexibility to changes in capacity or equipment and it is known that the shipper has some level of push strategy.
Carriers with large fleets (for large shippers).	When negotiating with large shippers, price higher if the carrier has a large fleet.
Carriers with recent fleets.**	Price higher if the carrier has recent fleets but be aware that a small group of shippers will expect low prices for this feature.**
* On average consolidated (LTL) services as less preferable (especially for high value shipments) but there is high variability on preferences (particularly for contracts with high volume of shipments)	
** There is variability on this trend as some shippers prefer older fleets.	

2.8 Acknowledgments

This research was possible thanks to the collaboration of a large number of transportation professionals that replied to the research invitation, responded to the survey, provided valuable feedback, and helped with contact information for survey distribution. Their support, time, and goodwill is deeply appreciated

2.9 Appendix - Heuristic to reduce cases from optimal design

For each attribute q , let ℓ_q be the corresponding set of levels, $n_l(q) \in n(q)$ the number of times that level $l \in \ell_q$ appears in the optimal design F , $n(q) = \{n_1(q), \dots, n_{|\ell_q|-1}(q)\}$ the set containing all such counts, and $\bar{n}(q) = |n(q)|^{-1} \sum_{l \in \ell_q} n_l(q)$ the mean of the counts. The variance for the counts for each attribute is presented in Equation (2.9).

$$\text{var}[n(q)] = \frac{\sum_{l \in \ell_q} (n_l(q) - \bar{n}(q))^2}{|n(q)| - 1} \quad (2.9)$$

Furthermore, a good-quality subset of $N < \bar{N}$ cases is the one that minimizes the objective function in Equation (2.10).

$$\min Z = \sum_{q=\{1, \dots, Q\}} \text{var}[n(q)] \quad (2.10)$$

The metaheuristic based on simulated annealing is presented in Algorithm 1. Simulated annealing (Chong and Zak, 2013) is a search procedure in which a new solution is searched in the neighborhood of the current one iteratively. In an iteration k there are two possibilities to update the current solution: (1) move to the new solution

with a probability $p_k = 1$ if the objective function of the new solution \tilde{Z}_{k+1} is less than the current one \tilde{Z}_k , or (2) move to the new solution with a probability $p_k = \exp -[(\tilde{Z}_{k+1} - \tilde{Z}_k)/T_k]$, where the so called temperature $T_k = \gamma/\ln(k + 2)$ is a positive sequence that reduces with the number of iterations, and the problem dependent constant γ is selected such that p_k is large enough to move to a solution with higher cost. K is a sufficiently large number of iterations. Notice that the probability of moving to the new solution associated to \tilde{Z}_{k+1} decreases as the difference $(\tilde{Z}_{k+1} - \tilde{Z}_k)$ increases and the number of iterations k increases, i.e. T_k decreases.

Algorithm 1: simulatedAnnealing (F, N, γ, K)

```

1   $k \leftarrow 0$ 
2   $\tilde{F}_k \leftarrow$  random sample of  $N$  choice sets from  $F$ 
3   $\tilde{Z}_k \leftarrow$  compute  $Z$  only for choice sets in  $\tilde{F}_k$ 
4   $\tilde{F}, \tilde{Z} \leftarrow \tilde{F}_k, \tilde{Z}_k$ 
5  While  $k \leq K$ 
6       $T_k \leftarrow \gamma/\ln(k + 2)$ 
7       $\tilde{F}_{k+1} \leftarrow$  random sample of  $N$  choice sets from  $F$ 
8       $\tilde{Z}_{k+1} \leftarrow$  compute  $Z$  only for choice sets in  $\tilde{F}_{k+1}$ 
9       $p_k \leftarrow \min\{1, \exp -(\tilde{Z}_{k+1} - \tilde{Z}_k)/T_k\}$ 
10      $r \leftarrow$  random number,  $r \in [0,1]$ 
11     If ( $r > p_k$ )
12          $\tilde{F}_{k+1}, \tilde{Z}_{k+1} \leftarrow \tilde{F}_k, \tilde{Z}_k$ 
13     If ( $\tilde{Z}_k \leq \tilde{Z}$ )
14          $\tilde{F}, \tilde{Z} \leftarrow \tilde{F}_k, \tilde{Z}_k$ 
15      $k \leftarrow k + 1$ 
16     If ( $0.75 * K \leq k < 0.75 * K + 1$ )
17          $\tilde{F}_k, \tilde{Z}_k \leftarrow \tilde{F}, \tilde{Z}$ 
18 Return  $\tilde{F}, \tilde{Z}$ 

```

CHAPTER 3. DEMAND CLUSTERING IN FREIGHT LOGISTICS NETWORKS

3.1 Introduction

Demand clustering in freight logistics networks is an important strategic decision for carriers. It is used to incorporate new business to their networks, detecting potential economies, optimizing their operation, and developing revenue management strategies. A specific example of demand clustering is truckload combinatorial auctions where carriers bundle lanes of demand and price them taking advantage of economies of scope. This research presents a novel approach to cluster lanes of demand based on historical sampling and a series of network transformations. Latin-hypercube sampling collects plausible scenarios based on historical information and dependence between shipment volumes and prices. Community detection is used to cluster the emergent network finding profitable collections of demand. Numerical results show the advantages of this method.

The concept of demand clustering has been approached in similar works in literature. Bidding advisory models have been developed to bundle lanes in TL combinatorial auctions (CA) (Song and Regan, 2003 and 2005, Wang and Xia, 2005, Lee, et al 2007). Additionally, geographic clustering has been used to reduce the computational complexity of vehicle routing problems (Bowerman et al., 1994, Bodin and Golden, 1981, Dondo and Cerda, 2007, Özdamar and Demir, 2012, Schönberger, 2006, Simchi-Levi et al. 2005).

Similarly, clustering has been used to understand the distribution of freight demand and simplify logistics operations (Cao and Glover, 2010, Sharman and Roorda 2011, Singh et al. 2007, Qiong et al, 2011). However, these works present several limitations. In many cases revenues are not considered -or highly simplified- when demand bundles are constructed. Furthermore, uncertainty related to lane price and volume is not captured. On the other hand, clustering approaches used in the past focus on geographic proximity that cannot capture network effects resulting from the complex interdependencies among lanes. The main objective of this chapter is proposing a systematic framework for demand clustering in freight logistics networks that overcomes these limitations.

This chapter is organized as follows. Section 3.1 introduces and motivates this research. Section 3.2 clearly defines the problem to be solved. Section 3.3 presents the methodology to solve it. Section 3.4 presents numerical results and advantages. Section 3.5 summarizes the work.

3.2 Problem definition

This section describes the economic relationships in freight logistics networks served by TL carriers. Then the problem to be solved is clearly defined.

In general, the clients of TL companies are known as Shippers. Let a lane be defined as the volume of truckloads per unit of time between an origin-destination (OD). Shippers are responsible for several lanes associated to their supply chains. They require transportation because they do not own transportation assets or because they own fleets but require additional capacity. TL carriers serve lanes of demand. A carrier can serve all or a subset of lanes for a specific shipper, and can work for many of them at the same time. TL companies operate over transportation networks (TNs). Their profits are

determined by the right combination of prices and operational costs. Variable costs are related to loading/unloading activities, loaded, and empty movements. Clearly, TL carriers are only paid for loaded movements. So, minimizing empty trips by guaranteeing follow-up loads is vital for profitable operations. Deploying vehicles in places where little freight originates is undesirable. Although fixed costs impact firm finances, Nagle et al. (2011) suggest that it is sufficient to consider variable costs only when developing effective revenue management strategies. So, fixed costs are not considered in the analysis. Successful carriers explore economies of scope by strategically serving demand with the right balance between volume and topology.

Uncertainty affects the operation of businesses because forecasted demand and prices are used to cluster demand based on vehicle routing strategies. However, if the actual demand significantly differs from the forecasted one there are economic losses and discontent from the carrier, who might compensate by reducing its level of service. This, in turn, affects the regular operation of the shipper and its supply chain. A good understanding of demand uncertainty helps the carrier developing proper clusters of demand. A highly competitive environment forces TL carriers to choose market prices that are significantly interrelated to lane volumes. These elements are affected by common sources of uncertainty.

Table 3.1 Mathematical notation

Notation	Definition
c_{od}	Traversing cost associated to each arc $(o, d) \in A$
D	Set of all lanes considered in the problem
\bar{D}	Set of current lanes served by the carrier $D \subset \bar{D}$
D^ℓ	ℓ^{tn} cluster of lanes. $D^\ell \subset D, \ell = 1, \dots, \mathcal{L}$
$F(x \mu, \sigma)$	Normal cumulative distribution function for mean μ and standard deviation σ
$f(o, d)$	Mapping from $o, d \in N$ to $i \in D$. $f: N^2 \rightarrow D$ such that demand in lane $i \in D$

Notation	Definition
	is picked-up at $o \in N$ and delivered at $d \in N$.
$G(N, A)$	Transportation network (TN) composed by a set of nodes N connected by the set of traversing arcs A
$\mathcal{G}(D, \mathcal{A})$	Demand super network composed by a set of demand nodes D connected by the set of traversing arcs \mathcal{A}
$g(i, j)$	Mapping from $i, j \in D$ to $d, o \in N$. $g: D^2 \rightarrow N^2$ such that $d \in N$ is the delivery node associated demand in lane $i \in D$ and $o \in N$ is the pickup node associated to demand in lane $j \in D$.
$h(i)$	Mapping from $i \in D$ to $o, d \in N$. $g: D \rightarrow N^2$ such that demand in lane $i \in D$ is picked-up at $o \in N$ and delivered at $d \in N$.
\mathcal{L}	Total number of clusters found by the algorithm
M	Number of samples selected for the Latin Hypercube Sampling process
σ	Numbers of historical observations of prices the corresponding shipment flows available to the carrier
P	$M \times D $ matrix of samples for each shipment price associated to lane $i \in D$.
\mathcal{P}	$\sigma \times D $ matrix of observations for each shipment price associated to lane $i \in D$.
\bar{p}	Vector of mean prices. $\bar{p} = \text{mean}(\mathcal{P})^t$
Q	$M \times D $ matrix of samples for each volume of shipments associated to lane $i \in D$.
\mathcal{Q}	$\sigma \times D $ matrix of observations for each volume of shipments associated to lane volume $i \in D$.
\bar{q}	Vector of mean volume of shipments. $\bar{q} = \text{mean}(\mathcal{Q})^t$
ς_i	Loading / unloading cost associated to serving lane $i \in D$
V	Covariance matrix for the observations $[\mathcal{P} \ \mathcal{Q}]$
v	Number of available vehicles (fleet size)
$W(D, \omega)$	Demand super network composed by a set of demand nodes D and a set of undirected weighted links ω (interconnections)
x_{ij}	Flow of trucks repositioned to serve demand $j \in D$ after serving demand $i \in D$. $(i, j) \in \mathcal{A}$
χ_{od}	Flow of trucks traversing arc $(o, d) \in A$

The problem solved by this research is clearly stated below. Table 3.1 summarizes mathematical notation. This Chapter considers a carrier serving a set of lanes \widehat{D} and looking for the possibility of incorporating new lanes $D \setminus \widehat{D}$ into its logistics operation (D are all lanes considered in the problem). For each lane $i \in D$ historical observations of shipment prices \mathcal{P}_i and lane volumes \mathcal{Q}_i are available. They are organized in the $\sigma \times |D|$ matrices \mathcal{P} and \mathcal{Q} respectively, where σ is the number of observations. The carriers operates over a TN $G(N, A)$, where, N are pickup/delivery nodes, and A are directed arcs

connecting these nodes. Arcs $(o, d) \in A$ are associated to traversing costs c_{od} (Loaded/Empty) and nodes $o, d \in N$ to pickup/delivery costs ζ_o, ζ_d . The carrier has a fleet of trucks of size v . Given these characteristics of the carrier and TN, we are asked to find the clusters of demand $D^\ell, \ell = 1, \dots, \mathcal{L}$ that represent increased expected profits for the carrier.

3.3 Methodology

This section presents preliminary concepts of carrier economies and network clustering. This justifies the proposed methodology, which is based on a series of methods applied over network transformations. Subsequently, the algorithmic framework to reveal hierarchical clusters in freight logistics networks is properly defined.

Finding groups of demand with synergetic properties in freight logistics networks is very important for strategic analysis, decision making, and business improvement at TL firms. However, detecting these lanes is not an easy task. Analysing the exponential number of all the possible combinations of lanes (Song and Regan, 2003), prices and desired volumes is a hard combinatorial problem known as the lane bundling problem, where demand is grouped based on complementary characteristics. This problem has been studied by bidding advisory models in TL CAs (Song and Regan, 2003 and 2005, Wang and Xia, 2005, Lee, et al 2007). The underlying concept behind lane bundling is achieving economies of scope (Caplice 1996, Jara-Diaz 1983, Jara-Diaz 1981).

Economies of scope are achieved by strategically positioning trucks such that follow-up loads are guaranteed and routing costs are distributed among several shipments. Backhauls are basic examples of economies of scope (Figure 3.1). If a truck delivers a

shipment from i to j with price p_{ij}^1 , cost c_{ij} , and returns empty to i (cost c_{ji}), the expected profit will be $\Pi^1 = p_{ij}^1 - (c_{ij} + c_{ji})$. However, if there is a backhaul (loaded return) the profit is $\Pi^2 = p_{ij}^1 + p_{ji}^2 - (c_{ij} + c_{ji})$ where any price p_{ji}^2 increases profits ($\Pi^1 \leq \Pi^2$).

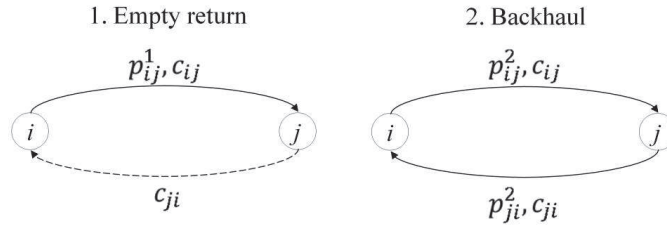


Figure 3.1 Example of economies of scope

In this work, the lane bundling problem is addressed using a clustering approach where subsets of elements sharing similar characteristics are grouped into clusters. In the last few years researchers and practitioners have used clustering methods to aggregate elements based on their proximity in multidimensional spaces, e.g., hierarchical, k-means, two-step, ad-hoc clustering, among others. Several vehicle routing problems (Bowerman and Calamai, 1994, Bodin and Golden, 1981, Dondo and Cerda, 2007, Özdamar and Demir, 2012, Schönberger, 2006, Simchi-Levi et al. 2005) take advantage of these methods by dividing the original network into subsets of geographically-close nodes where finding optimal routes is less cumbersome. Additionally, freight logistics problems have used clustering to understand the geographic distribution of demand and simplify logistics operations (Cao and Glover, 2010, Sharman and Roorda 2011, Singh et al. 2007, Qiong et al, 2011) However, there are three limitations when proximity-based methods are used to cluster elements with an underlying network structure (Fortunato, 2010): (1) clustering points in a network requires at least a similarity metric for each pair of nodes,

so storage space grows exponentially, (2) defining metric spaces to describe proximity in graphs is not trivial and significantly increases computational complexity, and (3) numerical experiments show that clusters highly depend on the type of metric defined.

Community detection algorithms (CDAs) (Girvan and Newman, 2002; Blondel et al., 2008, Fortunato, 2010) overcome this limitation. They are developed to unmask highly interconnected elements in a network. Although they have been used to analyse several complex networks (e.g., social and biological networks, the World Wide Web, the international trade network), they are scarcely used in transportation applications. Nejad et al. (2012) is one of the few examples of using CDAs to understand transportation problems. To the best of the authors' knowledge, community detection has neither been used in trucking research nor for the lane clustering problem. Nonetheless, CDAs are extremely important to consider network effects between lanes, i.e., economies of scope.

Applying CDAs in this context requires defining the elements to cluster and their level of interconnectivity. In this work these elements are lanes. For each pair of lanes the interconnectivity metric is defined as the utility of having them in the same cluster, i.e., served by the same trip-chain. Fan et al. (2006) also propose using utility functions to determine the proximity of clustered vehicles in vehicular ad-hoc networks (VANETS). They hypothesize utility functions based on available information. However, in this research utility is not explicitly available in the original TN. Hence, a series of network transformations are required to construct an interconnectivity network (IN) suitable for community detection.

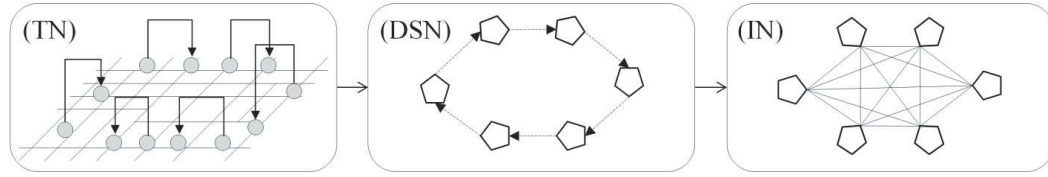


Figure 3.2 Conceptual representation of network transformations.

An algorithmic approach is proposed to solve the problem in Section 3.2, which is based on a series of network transformations illustrated in Figure 3.2. Table 3.2 summarizes the pseudo code for the main algorithm which is supported by four modules. Intuitively, the TN is composed by a set of nodes (pickup or delivery according to the lane distribution). Directed arcs between these nodes indicate traversing costs for loaded and empty trips (repositioned after delivering). Likewise, each shipment in a lane is associated to a price and pickup/delivery costs. Historical observations of prices and demand are used to design a number of scenarios according to their likelihood of occurrence and joint dependency. This is achieved using a Latin hypercube sampling method that accounts for dependency among sampled variables, i.e., price and demand level. Each sample determines an instance of prices and demand (truck volume) for the analysed lanes. For each instance, a demand super network (DSN) -where nodes are lanes and directed arcs represent the repositioned flow of trucks between lanes- is constructed. A profit maximization linear program (LP) is used to find the optimal distribution of loaded and empty trips in the DSN. Each lane can be part of a trip-chain that connects several lanes and provides economies of scope to the carrier. However, there are two issues for proper demand clustering at this point: (1) flows are aggregated so it is not possible to differentiate trip-chain, and (2) -assuming trip-chains can be found- there is no

evident connection between all lanes in a trip-chain (only the downstream and upstream connections are known). So, a novel method is proposed to detect and disaggregate trip-chains, i.e., tours composed by synergetic lanes in the DSN. The joint utility between every pair of demand in these tours is computed and used to generate an interconnectivity network (IN) where each pair of lanes is weighted using the bilateral utility of having them in the same tour. This network is updated after running each sampled scenario. Then, when all scenarios are explored, a CDA is applied over the IN taking advantage of the rich information accumulated by the sampling process and revealing the corresponding clusters of profitable demand.

Table 3.2 Main algorithm: demand clustering in freight logistics networks

Step	Description	
1	$\bar{p}, \bar{q}, V \leftarrow \text{mean}(\mathcal{P})^T, \text{mean}(\mathcal{Q})^T, \text{cov}([\mathcal{P} \ \mathcal{Q}])$	
2	$[P \ Q] \leftarrow \text{latinHypercubeSampleNormal}\left(\begin{bmatrix} \bar{p} \\ \bar{q} \end{bmatrix}, V, M\right)$	Module 1
3	$\omega \leftarrow D \times D $ matrix: $\omega_{ij} = 0$	
4	For $m = 1, \dots, M$	
5	$p^T, q^T \leftarrow m\text{th row of } P, m\text{th row of } Q$	
6	$x^m \leftarrow \text{demSupNetLP}(c_{od}, \varsigma_i, \hat{D}, p, q, \nu)$	Module 2
7	$\omega \leftarrow \omega + \text{updateInterconnections}(x^m, p, c_{od}, \varsigma_i)$	Module 3
8	End	
9	If ($\omega_{ij} < 0$)	
10	$\omega_{ij} \leftarrow 0$	
11	Else	
12	$\omega_{ij} \leftarrow \frac{\omega_{ij}}{m}$	
13	End	
14	$D^1, \dots, D^\mathcal{L} \leftarrow \text{clustering}(\omega)$	Module 4
15	Return $D^1, \dots, D^\mathcal{L}$	

Formally, the algorithm starts by computing the mean \bar{p}, \bar{q} and covariance V of historical observations \mathcal{P} and \mathcal{Q} to generate M dependent samples from a Latin Hypercube sampling process, i.e., $P \in \mathbb{R}^{M \times |D|}$ and $Q \in \mathbb{R}^{M \times |D|}$ (Module 1). A sufficiently large number of samples M is defined by the modeler. For each sample $m \in \{1, \dots, M\}$ an instance of DSN is generated and a profit maximization network flow LP is solved to find the optimal distribution of trucks x^m that maximizes carriers profits (Module 2). Then, each resulting trip-chain is fathomed to determine the utility between duplets of lanes ω_{ij} and update the IN (Module 3). After properly standardizing ω_{ij} , a CDA is used to unmask the demand clusters D^ℓ (Module 4).

3.3.1 Module 1: Latin hypercube sampling with dependent variables

A sampling process is used to replicate stochastic demand and prices. Sampling is a common technique in experiment design and scenario testing. The Monte Carlo method (Metropolis & Ulam, 1949) is a popular procedure but it is expected to generate biased samples. The Latin hypercube sampling (McKay et al., 1979; Iman et al., 1981) overcomes this limitation by evenly distributing the multidimensional space (Latin hypercube) and selecting samples from each subdivision. However, this approach cannot capture flow and price dependency which is important as trucking volumes and prices are not independent. For example, fluctuations in the flow of trucks delivering the final demand of a product proportionally affect the movement of goods in the upstream supply chain. Similarly, economies of scope correlate prices and volumes, e.g., high volume of truckloads in one direction and low volume in the opposite one might result in lower prices for the backhauls. Stein (1987) proposes a variation of the Latin hypercube

sampling that considers dependency between variables. Therefore, that method is used in this module.

Table 3.3 Module 1: Latin hypercube sampling with dependent variables

Step	Description
1.1	$z \leftarrow M \times \mu $ matrix where each row is a sample with multivariate normal distribution (μ, V)
1.2	$\phi \leftarrow M \times \mu $ matrix where ϕ_{ij} correspond to the ranking of z_{ij} in the j th column of z
1.3	$\phi \leftarrow (\phi - 0.5)/M$
1.4	$y \leftarrow m \times \mu $ matrix where y_{ij} corresponds to:
	$y_{ij} \leftarrow y_{ij}: \phi_{ij} = F(y_{ij} \mu_j, \sqrt{V_{jj}}) = \frac{1}{\sqrt{2\pi V_{jj}}} \int_{-\infty}^{y_{ij}} e^{-\frac{(t-\mu)^2}{2V_{jj}}} dt$
1.5	Return y

Table 3.3 summarizes the pseudo code for this module. The vector of average values $\mu = [\bar{p}^T \bar{q}^T]^T$ and the corresponding covariance matrix V are used to generate M samples from a multivariate normal distribution $z \in \mathbb{R}^{M \times |\mu|}$. These values are ranked column-wise to divide the space into M independent subdivisions, which are standardized in the interval $[0,1]$ and assigned to the middle of each range $\phi \in \mathbb{R}^{M \times |\mu|}$. Finally, the matrix of samples $y = [P \ Q] \in \mathbb{R}^{M \times |\mu|}$ is populated using the values y_{ij} for which the normal cumulative distribution function $F(y_{ij} | \mu_j, \sqrt{V_{jj}})$ is equivalent to ϕ_{ij} .

3.3.2 Module 2: demand super network linear program

This module constructs the DSN first and then solves a network-flow LP to find the flow of trucks that maximizes profits in this network.

Table 3.4 Module 2: demand super network linear program

Step	Description
2.1	$u \leftarrow D \times D $ matrix where $u_{ij} = p_j - c_{g(i,j)} - c_{h(j)} - \varsigma_j$
2.2	Solve the following linear program
2.2.1	$\max \sum_{(i,j) \in \mathcal{A}} u_{ij} x_{ij}$
2.2.2	s.t.
2.2.3	$\sum_{i \in D} x_{ij} = \sum_{i \in D} x_{ji} \quad \forall j \in D$
2.2.4	$\sum_{i \in D} x_{ij} = q_j \quad \forall j \in \widehat{D}$
2.2.5	$\sum_{i \in D} x_{ij} \leq q_j \quad \forall j \in D \setminus \widehat{D}$
2.2.6	$\sum_{i \in D} x_{ij} \leq v \quad \forall j \in D$
2.2.7	$x_{ij} \geq 0 \quad \forall (i,j) \in \mathcal{A}$
2.3	Return x

Table 3.4 summarizes the pseudo code for this module. Let $\mathcal{G}(D, \mathcal{A})$ be the DSN where the set of super nodes corresponds to the set of lanes D . Nodes in D are connected by a set of directed arcs \mathcal{A} , where $(i, j) \in \mathcal{A}$ represents the trucks repositioned to serve demand $j \in D$ after serving demand $i \in D$. The following network transformations are illustrated in Figure 3.3. Each arc is associated to a repositioning utility defined as $u_{ij} = p_j - c_{g(i,j)} - c_{h(j)} - \varsigma_j$, where p_j is the current sampled price and ς_j is the loading/unloading costs for lane $j \in D$, $c_{g(i,j)} = c_{d_i o_j}$ is the traversing cost of a truck repositioned from $d_i \in N$ (Node where demand $i \in D$ is delivered) to $o_j \in N$ (Node where demand $j \in D$ is picked up), and $c_{h(j)} = c_{o_j d_j}$ is the traversing cost of a truck serving the downstream demand $j \in D$ picked up at $o_j \in N$ and delivered at $d_j \in N$. The mapping functions $g(i, j) = (d_i, o_j) \in A$ and $h(j) = (o_j, d_j) \in A$ are conveniently defined to make transformations between $\mathcal{G}(D, \mathcal{A})$ and $G(N, A)$.

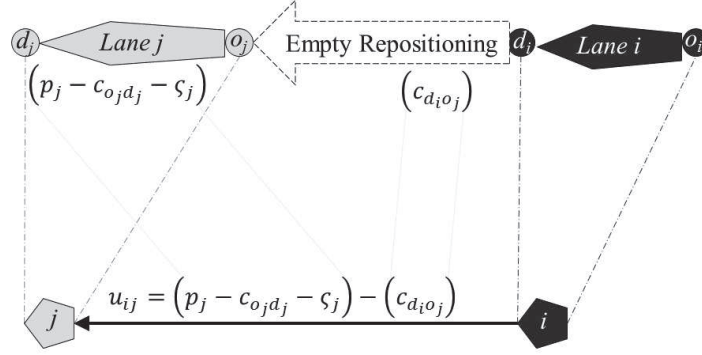


Figure 3.3 Arc representation in the DSN and its relationship with the TN.

Subsequently, the LP in line 2.2 (Table 3.4) is solved. Here, the variables x_{ij} represent the flow of repositioned trucks. The objective function (line 2.2.1) maximizes the utility associated to the deployment of x over $\mathcal{G}(D, \mathcal{A})$ such that: there is flow conservation for the trucks serving each lane $j \in D$ (line 2.2.3), demand in the set of lanes currently served by the carrier \widehat{D} must be served (line 2.2.4), demand in the set of potential lanes to be included in the carrier network $D \setminus \widehat{D}$ are optionally served (line 2.2.5), there is a limited availability of trucks ν to serve the network (line 2.2.6), and non-negativity of x_{ij} (line 2.2.7). Notice that this LP can efficiently be solved by regular commercial software, e.g., CPLEX.

3.3.3 Module 3: update interconnections

This module finds each tour in the network and relates each duplet of demand $i, j \in D$ with a weight ω_{ij} in the IN. The pseudo code presented in Table 3.5 describes this process. First each flow x_{ij} in the DSN is associated with the corresponding flows in the TN, i.e. $\chi_{g(i,j)} = \chi_{d_i o_j}$ and $\chi_{h(i)} = \chi_{o_i d_i}$. Then arcs A in the TN are locally modified to consider only arcs with flow. The main loop searches trip-chains in the network. At each

iteration, the arc $(s, r) \in A$ with less flow χ_{sr} is selected and removed from A . Then, the shortest path T from r to s is computed. Its cost is $c(T)$. Each flow χ_{ij} associated to arcs in T , and arc (s, r) itself is reduced by χ_{sr} . Subsequently a set of lanes \mathcal{T} is generated to hold the demand elements associated to $T \cup \{(s, r)\}$. Notice that the mapping function $f(o_i, d_i) = i \in D$ is used to map elements from $G(N, A)$ to $\mathcal{G}(D, \mathcal{A})$. Then, the average cost associated to each element in \mathcal{T} is computed and the interconnectivity between elements in each tour is updated by adding the fractional income associated to the demand objects i and j minus the corresponding average cost.

Table 3.5 Module 3: update interconnections

Step	Description
3.1	$\chi \leftarrow N \times N $ matrix
3.2	$\chi_{g(i,j)} \leftarrow \chi_{g(i,j)} + x_{ij} \forall (i,j) \in \mathcal{A}$
3.3	$\chi_{h(i)} \leftarrow \chi_{h(i)} + x_{ij} \forall (i,j) \in \mathcal{A}$
3.4	$A \leftarrow \emptyset$
3.5	$A \leftarrow A \cup \{(o, d), \forall o, d \in N: x_{od} > 0\}$
3.6	$\omega \leftarrow D \times D $ matrix: $\omega_{ij} = 0$
3.7	While ($\max(x) > 0$)
3.8	$(s, r) \leftarrow \operatorname{argmin}(\chi_{od}: (o, d) \in A)$
3.9	$A \leftarrow A \setminus \{(s, r)\}$
3.10	$T, c(T) \leftarrow$ compute shortest path from $r \in N$ to $s \in N$ over $G(N, A)$ using cost matrix c . Return path $T \subset A$ and its corresponding cost $c(T)$.
3.11	$\chi_{od} \leftarrow \chi_{od} - \chi_{sr}, \forall (o, d) \in T \cup \{(s, r)\}$
3.12	$\mathcal{T} \leftarrow \emptyset$
3.13	$\mathcal{T} \leftarrow \mathcal{T} \cup \{f(o, d) \in D, \forall (o, d) \in T \cup \{(s, r)\}\}$
3.14	$\bar{c}(\mathcal{T}) \leftarrow \chi_{sr} \frac{c(T) + c_{sr}}{ \mathcal{T} }$
3.15	If ($ \mathcal{T} = 1$)

Step	Description
3.16	$\forall i \in \mathcal{T}: \chi_{sr}(p_i - \varsigma_i) - \bar{c}(\mathcal{T}) > 0$ $\omega_{ii} \leftarrow \omega_{ii} + \chi_{sr}(p_i - \varsigma_i) - \bar{c}(\mathcal{T})$
3.17	Else
3.18	$\forall i, j \in \mathcal{T}: i < j, \chi_{sr} \frac{(p_i + p_j) - (\varsigma_i + \varsigma_j)}{ \mathcal{T} - 1} - \bar{c}(\mathcal{T}) > 0$ $\omega_{ij} \leftarrow \omega_{ij} + \chi_{sr} \frac{(p_i + p_j) - (\varsigma_i + \varsigma_j)}{ \mathcal{T} - 1} - \bar{c}(\mathcal{T})$
3.19	End
3.20	End
3.21	Return ω

3.3.4 Module 4: clustering

Module 4 (described by the pseudo code in Table 3.6) applies the community detection algorithm presented in Blondel et al. (2008). This algorithm is based on modularity maximization. It has been successfully and efficiently used to detect network clusters in several applications. The main input for this algorithm is the interconnectivity matrix ω , which is first added to its transpose to standardize directed weights to the undirected case. The algorithm starts assigning each demand i to a cluster D^i . Then, initial clusters are recomputed based on modularity maximization sub-module (Sub-module 5). Next, the main while loop runs and sequentially aggregates clusters up to finding the configuration with the maximum modularity.

Table 3.6 Module 4: clustering

Step	Description
4.1	$\omega \leftarrow \omega + \omega^T$
4.2	$D^i \leftarrow \{i\}, \forall i \in D$
4.3	$\tau \leftarrow 0$

Step	Description	
4.4	$\theta_\tau \leftarrow 0$	
4.5	$\theta_{\tau+1}, D^\ell \leftarrow \text{computeModularity}(\omega, D^i)$	Sub-module 5
4.6	While ($\theta_{\tau+1} > \theta_\tau$)	
4.7	$\tau \leftarrow \tau + 1$	
4.8	$D \leftarrow \{i: D^i \neq \emptyset\}$	
4.9	$\omega \leftarrow D \times D $ matrix. $\omega_{ij} = 0$	
4.10	$\omega_{ij} \leftarrow$ Weight of links between D^i and D^j	
4.11	$D^i \leftarrow \{i\}, \forall i \in D$	
4.12	$\theta_{\tau+1}, D^\ell \leftarrow \text{computeModularity}(\omega, D^i)$	Sub-module 5
4.13	End	
4.14	Return $D^1, \dots, D^\ell, \dots$	

Since carriers are interested in detecting new clusters inside previously found clusters, for every cluster D^ℓ Module 4 is recursively applied. Thus, the initial clusters are defined as mega-clusters (MC). Each MC is composed by several interior sub clusters (SC). Consecutively, interior SCs are composed by smaller SCs and so on. This hierarchical clustering groups lanes in several strata.

3.3.5 Sub-module 5: compute modularity

This sub-module (Table 3.7), which is also described in Blondel et al. (2008), iteratively swaps nodes between clusters. When there is increment in modularity $\Delta\theta'$ by adding a node i to a cluster D^λ this action is performed. The process stops when modularity cannot be increased. Although this is a greedy approach, it has shown to be very efficient in practical settings.

Table 3.7 Sub-module 5: compute modularity

Step	Description
5.1	$g \leftarrow 1$
5.2	While($g = 1$)
5.3	$g = 0$
5.4	For $i = 1, \dots, D $
5.5	$\Delta\theta \leftarrow 0$
5.6	$\lambda \leftarrow \{\lambda \in D: i \in D^\lambda\}$
5.7	For $j = 1, \dots, D : \omega_{ij} > 0, j \in D^\ell, D^\ell \cap \{i\} = \emptyset$
5.8	$\dot{k}_{rs} \leftarrow \sum_{r,s \in D^\ell} (\omega_{rs})$
5.9	$\check{k}_{is} \leftarrow \sum_{s \in D^\ell} (\omega_{is})$
5.10	$K \leftarrow 1/2 \sum_{r,s \in D} (\omega_{rs})$
	$k_{rs} \leftarrow \sum_{r \in D} \sum_{s \in D^\ell} (\omega_{rs})$
5.11	$\hat{k}_{ri} \leftarrow \sum_{r \in D} (\omega_{ri})$
5.12	$\Delta\theta' \leftarrow \left[\frac{k_{rs} + 2\check{k}_{is}}{2K} + \left(\frac{k_{rs} + \hat{k}_{ri}}{2K} \right)^2 \right] - \left[\frac{k_{rs}}{2K} - \left(\frac{k_{rs}}{2K} \right)^2 - \left(\frac{\hat{k}_{ri}}{2K} \right)^2 \right]$
5.13	If($\Delta\theta < \Delta\theta'$)
5.14	$\Delta\theta \leftarrow \Delta\theta'$
5.15	$\lambda \leftarrow \ell$
5.16	$g = 1$
5.17	End
5.18	End
5.19	End
5.20	End
5.21	$\theta_{\tau+1} \leftarrow \frac{1}{2K} \sum_{i,j \in D} \left(\omega_{ij} - \frac{\hat{k}_{ri}\hat{k}_{rj}}{2K} \right) \delta(i,j), \delta(i,j) = \begin{cases} 1, & \text{if } i,j \in D^\ell \\ 0 & \text{otherwise} \end{cases}$
5.22	Return $\theta_{\tau+1}, D^\ell$

In summary, clusters of lanes are found using interdependent historical information for volume and price on every lane. Latin-hypercube is used to sample dependent volume/price scenarios. The optimal distribution of flow between lanes is determined for

each sample solving a profit maximization LP. Synergetic lanes are interconnected based on their bilateral utility generating an interconnectivity network that is updated iteratively. Finally, community detection is used to cluster the network that emerges and finding profitable demand collections. An important benefit of this method that it is flexible to be implemented in well-known programming platforms like Matlab, Python, C++, Java, among other. Furthermore, each module can be either developed or borrowed from available open sources or commercial software. For example, Latin hypercube sampling is available in platforms like Matlab, R, Python, SAS/JMP, etc. Linear programming can be solved using commercial software, e.g., AMPL/CPLEX, ILOG CPLEX, Gurobi, Lindo, Gams, Matlab, etc. Source code for community detection algorithms is available for Matlab, C++, Python, among other, and implemented in several network analysis software, e.g., NetworkC and Gephi.

3.4 Numerical results

This section presents a numerical example to illustrate the methodological framework. Then, a numerical experiment is performed to test its scalability. The suite of algorithms is coded in Matlab and run in an average desktop with Inter ® Core 2 Duo Processor (E8400) at 3.00 GHz and 4.00 GB of RAM. The open source code developed by Scherrer and Blondel (2014) is used for community detection.

For the numerical example consider the TN in Figure 3.4(a). Each arc in the grid network has unitary cost. Without loss of generality assume that the cost for each lane (traversing plus loading/unloading) is equivalent to the sum of unitary costs for covered arcs. Repositioning costs correspond to the shortest path between lanes in the grid network. Currently, the carrier serves $|\widehat{D}| = 21$ lanes and is considering other 21 lanes

for new businesses. In total, this analysis considers $|D| = 42$ lanes. A number of $\sigma = 100$ contemporaneous observations for price \mathcal{P} and shipment volume \mathcal{Q} are available for each lane. The mean $[\bar{p}, \bar{q}]$ and covariance V for these values are illustrated in Figure 3.4 (b).

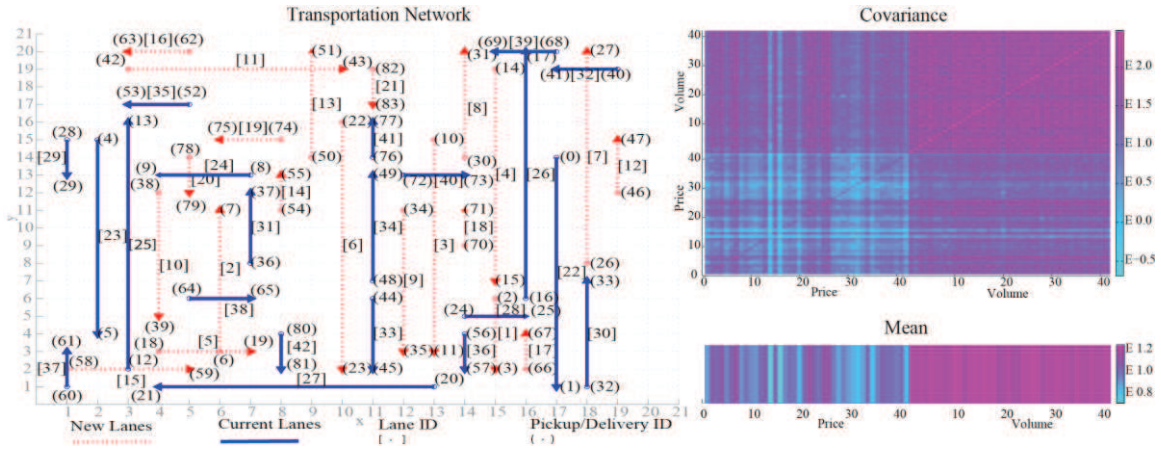


Figure 3.4 Numerical example: (a) TN and demand (left), (b) mean and covariance for price and truck volumes (right).

The carrier selects $M = 100$ samples to undertake the analysis (Module 1). For each sample, the linear program in Module 2 is solved and the IN populated (Module 3). Figure 3.5 presents the resulting IN and shows that several lanes present synergies when operated together. However, these synergies are stronger for groups of them. For example, the new lane 7 is strongly related to the current lane 22, which is intuitive by the directionality of the flows in in Figure 3.4(a). Furthermore, current lanes 30 and 32 complement these movements by reducing empties. Notice that the geographic position of 30 and 32 results in no direct interconnection between them but they have strong common allies, i.e., 7 and 22. Similarly, the new lane 15 forms a strong triplet with lanes 23 and 25 giving continuity to the current traffic flows. On the other hand, there are isolated lanes with scarce interconnections but strong connectivity to themselves, i.e.,

new lane 19 and current lanes 29, 35, 41. These lanes are characterized by backhaul movements and this can happen for several reasons, e.g., they are isolated or peripheral in the network, the topological characteristics of lanes in their neighbourhoods are not suitable for follow-up loads, neighbour lanes have stronger synergy with other lanes in the system. Interestingly, lane 29 has no interconnections but its self-strength is extremely high, i.e., it has no synergy but is very valuable for the carrier. This is because it is a profitable but peripheral lane. Other groups of lanes hidden in the IN are mined using community detection (Module 4).

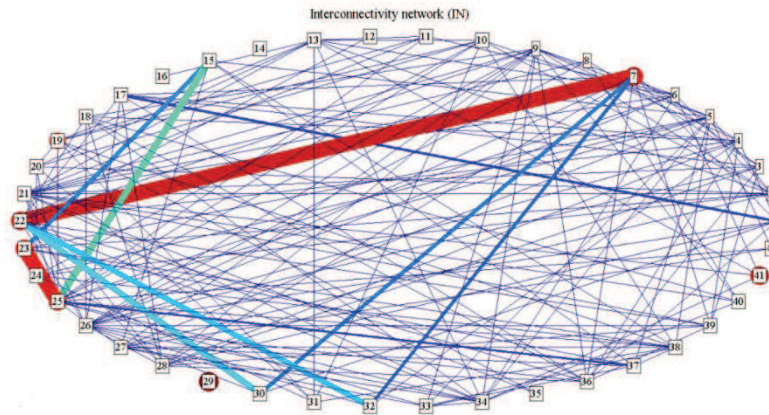


Figure 3.5 Numerical example: IN.

The clustering algorithm reveals seven MCs (Figure 3.6(a)). Community detection reinforces the intuition presented below by unmasking synergies not distinguishable by observation. 22 MCs are observed, i.e., 7 aggregating more than two lanes and 15 are singletons. MC 1 is composed by lanes 7, 22, 30, 32 as noticed above. Synergies are complemented by the new lanes 4, 8, 3 and current lanes 26, 39. MC 2 is composed by lanes 15, 23, 25 -noticed before- and complemented with the current lane 37. Other clusters are MC 3 composed by new lanes 18, 9, 6, current lane 34, MC 4 by new lanes

11, 13, 16 only, MC 5 by new lanes 5, 2, current lane 27, by new lanes 1,17 only, MC 7 by new lane 20, current lane 24. Each of the remaining lanes is a cluster itself. Lanes 19, 29, 35, 41, mentioned above, are in this category. Interestingly, many current lanes are benefited by adding new lanes. On the other hand, clusters composed only by new lanes represent new business opportunities for the carrier.

The hierarchical structure of the clusters is obtained by fathoming MCs. Figure 3.6(b) show the composition of the MCs and their corresponding SCs. MC 1 is divided in two SCs: SC 1.1 with strong interconnected lanes and SC 1.2 with other interconnected lanes that have less strength, MC 2 segregates lane 37 and creates SC 2.1 with the strong triad 15, 23, 25. Furthermore, lanes 18 and 5 are separated from M3 and M5 creating new SCs. MCs 4, 6, 7 are strong by themselves and no disaggregation is needed. This example shows that analysing the freight demand clustering problem is considerably complex even for small instances. The proposed methodology reduces this complexity and is a viable alternative for carriers that face large instances of this problem in their regular operations.

The scalability of the method is tested with a numerical experiment. The number of samples in the experiment is set to $M=100$. The geography of the transportation network is randomly generated with traversing cost equal to the Euclidean distance between nodes. Likewise, the set of lanes D and the corresponding sets of observation P and Q are synthetically generated following appropriate ranges avoiding inconsistencies. Table 8 summarizes the experiment where demand varies from 25 to 500 lanes and the corresponding pickup/delivery nodes go from 50 to 1000.

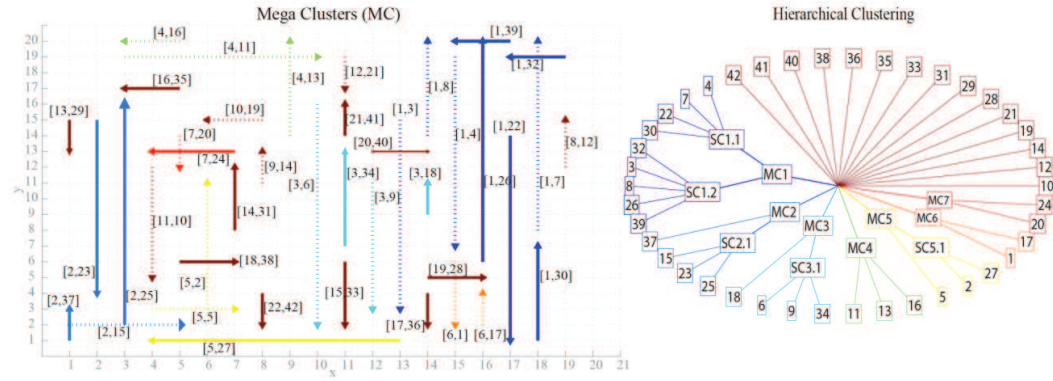


Figure 3.6 Numerical Example: (a) MCs of demand (notation: [MC ID, lane ID]) (left), (b) hierarchical clustering (right).

Table 3.8 shows that the method is suitable for sufficiently large instances. The modules that are spending the most computational time are the one related to the solution of the LP (Module 2) and the one where trip-chains are searched to update the IN (Module3). Likewise, modularity and number of clusters increases as the number of demand objects increases. In general, the number of MCs (computed before starting the recursive process described in Module 4) represents a large proportion of the total clusters found.

Table 3.8 Scalability experiments

Demand	Nodes	MCs	Modularity	Total clusters	Inputs	Module 1	CPU Time (seconds)			Total
							Module 2	Module 3	Module 4	
25	50	6	0.71	12	0.00	0.00	2.76	1.56	1.08	5.40
50	100	21	0.83	32	0.11	0.02	8.44	7.46	1.19	17.21
100	200	30	0.83	47	0.03	0.05	30.09	40.06	5.51	75.74
200	400	108	0.83	135	0.47	0.31	189.17	233.03	19.00	441.98
500	1000	284	0.90	340	1.22	4.06	2836.70	3212.40	28.83	6083.20

There are several key insights from these results. Network effects must be considered when clustering freight demand. Although geographic proximity highly impacts

clustering, it is not the only and most important attribute. Bilateral utility between lanes determines their actual proximity, which is a function of the trip-chains encompassing them. Thus, topology (geography and directionality), shared profits (volumes, costs, and prices), and contemporaneity, are key elements for demand clustering in freight logistics networks affected by uncertainty. High bilateral utility is a key trait for clustering demand but it is not sufficient. The strength and degree of interconnectivities between lanes determine their actual closeness, in social networks jargon: “the friend of your friend is likely also to be your friend” (Newman, 2003). Furthermore, lanes complement at different levels. Those with higher synergies remain together over several sub-clusters. Lanes with less strength either disconnect leaving the stronger elements clustered, or agglomerate into new sub clusters with other synergetic lanes. Not all lanes are synergetic in the system. Some of them are not suitable to be clustered and they operate better alone. This happens because they are distant, i.e., geographically far, with opposite directionalities, or not competitive with respect to other lanes already clustered. Finally, the method is suitable for real world applications where large number of lanes need to be analysed.

3.5 Conclusions

This research considers the problem of clustering lanes of demand in freight logistics networks. This is motivated by the economies of scope achieved by important logistics clusters implemented over the world. Demand clustering is relevant for flexible transporters that need to identify groups of synergetic lanes. These lanes should be profitable under uncertain volumes and prices. Empty-trip reduction is critical to achieve this goal because it considerably decreases operational costs. Furthermore, this

phenomenon mitigates negative externalities to society. The clustering problem is approached from a truckload (TL) perspective. TL is the most popular and flexible type of operation for freight transportation.

Demand clustering in logistics networks is important for several reasons. First, it facilitates the analysis and prioritization of demand for TL carriers, which is essential to detect new business opportunities that can be included into their current networks efficiently. Thus, clusters have to be carefully built in order to add synergies that reduce empties and increase profits. Furthermore, optimizing routing and scheduling over the complete network covered by large carriers is computationally demanding. An appropriate clustering approach is vital to detect sub-networks that can be optimized efficiently. Finally, knowledge about lanes that perform well when served together is important to develop pricing and revenue management strategies that add value to the business of their clients, i.e., shippers. For example, two lanes from two separate shippers served in isolation would be individually expensive. However, if economies of scope are achieved and they are part of the same cluster, the carrier can price them lower without monetary losses. This makes the current service competitive (low price), and reduces transportation expenses for the shippers.

This Chapter proposes a novel algorithmic approach to cluster lanes of demand, which is based on dependent sampling over historical data and a series of network transformations. Briefly, Samples for price and volume are collected using the Latin-hypercube technique. A profit maximization linear program is solved to find the optimal distribution of trucks associated to each sample. Based on these flows, trip-chains are mined to determine the bilateral utility of synergetic lanes. Finally, these utilities are used

to populate an interconnectivity network, which is explored with a community detection algorithm to cluster demand lanes. The main contributions of this work are (1) proposing a novel framework to consider interdependencies between lanes, (2) incorporating market prices in a revenue management fashion, (3) considering the interrelation and variability of lane volumes and prices, (4) developing an algorithmic approach that is computationally efficient.

Numerical experiments show the importance of the method. Geographic nearness is not the only attribute to consider when clustering demand in logistics networks. The contemporaneous bilateral utility determined by the profit of serving lanes in the same trip-chain is an accurate metric of proximity that takes into account the different dimensions of this complex problem. Additionally, this Chapter shows that lanes present synergies at different levels, i.e., in a hierarchical fashion. Thus, carriers can analyze the opportunities of serving combinations of lanes with different priorities, which is important for decision making in complex networks. Consequently, in some cases, it is better not to consider some lanes that are in the vicinity of others but do not contribute to their local synergy. The model is scalable for real world applications.

CHAPTER 4. PRICING AND BUNDLING TRUCKLOAD SERVICES WITH DETERMINISTIC DEMAND

4.1 Introduction

Constructing bundles, e.g., for truckload combinatorial auctions, is a challenging problem faced by trucking firms. Several bidding advisory models have been proposed to bundle lanes considering their synergetic effects. These models are based on cost minimization approaches. However, they do not capture pricing and demand segmentation. Pricing is a key competitive advantage that maximizes profits when it is properly combined with cost minimization. Similarly, demand segmentation allows carriers to fully benefit from these auctions. This chapter introduces BM \circ T, a bidding advisory model for truckload combinatorial auctions that can be used by trucking practitioners to bundle lanes and overcome these limitations. Numerical experiments show the benefits and efficiency of the algorithmic framework.

As shown in Subsection 1.2.3, a revenue management strategy that properly combines low cost bundles with prices that maximize the expected profits of carriers participating in TL CA is missing in literature. Consequently, in new TL CA carriers are allowed to bid for segments of demand in the lane rather than all of it. This is important for carriers because they can bid for volumes that give them more economies. On the other hand, shippers prefer to split high volume lanes into several carriers in order to add robustness to their businesses.

This work introduces BM◦T (Bidding model for TL demand), a computational package that overcomes the limitations of available bidding advisory models. Two contributions demonstrate the superiority of BM◦T over previous approaches: (1) it handles bundle generation and pricing explicitly, (2) it determines the amount of flow that the carrier is willing to serve in each bundle.

The chapter is organized as follows. Section 4.1 introduces and motivates the problem. Section 4.2 clearly defines the problem to solve. Section 4.3 presents the methodology proposed to solve it (BM◦T), which is visualized with operational examples in Section 4.3.4. Section 4.5 concludes the chapter.

4.2 Problem definition and formulation

This section clearly defines the problem to be solved. Intuitive definitions are followed by formal notations that describe the problem. Then the problem is formulated as a mixed integer quadratic program (MIQP). General mathematical notation is summarized in Table 4.1.

A shipper that requires moving volumes of shipments between different origins and destinations organizes a TL CA. There is a reservation price that shipper is willing to pay for each lane. The shipper communicates lane information related to geographies, volumes, and maximum prices to a group of carriers invited to the auction. Each carrier is responsible for reviewing these data and constructing bids (quotes) that are submitted back to the shipper. Each bid is a bundle of desired lanes. Bundles are accompanied with the following information: desired volume and charged price. Desired volume indicates the maximum TL volume that the carrier is willing to serve for lanes in the package. Price indicates the amount charged for each TL shipment included in the bundle. After

collecting all bundles from all carriers, the shipper analyzes this information and awards the most competitive bundles to the corresponding carriers. Finding the best combination of bundles/carriers that reduces total transportation procurement cost for the shipper is formally called: the winning determination problem (WDP). When a carrier is awarded for a bundle, it wins the right and priority to serve the shipments in it.

Table 4.1 General mathematical notation

Notation	Definition
D	Set of lanes auctioned in the TL CA. Each lane $(i, j) \in D$ associated to demand q_{ij} and reservation TL price \bar{p}_{ij} .
q_{ij}	Demand of TL per unit of time associated to the auctioned lane $(i, j) \in D \subset A$.
\bar{p}_{ij}	Reservation TL price (\$) for to the auctioned lane $(i, j) \in D$.
B	Set of bundles submitted by a carrier to the auction. Each bundle $b \in B$ associated to auctioned lanes $\beta_b \subset D$, maximum desired demand x_b , and TL price p_b .
β_b	Set of auctioned lanes included in bundle $b \in B$. $\beta_b \subset D$.
x_b	Maximum amount of demand (TL per unit of time) the carrier is willing to serve in bundle $b \in B$. $x_b \leq q_{ij} \forall (i, j) \in \beta_b$.
p_b	Price the carrier would charge for every TL in bundle $b \in B$ if awarded by the shipper. $p_b \leq \bar{p}_{ij} \forall (i, j) \in \beta_b$.
\widehat{D}	Set of lanes currently served by the carrier. Each lane $(i, j) \in D$ associated to demand f_{ij} and a current TL price \hat{p}_{ij} .
f_{ij}	Demand of TL per unit currently served by the carrier in the lane $(i, j) \in \widehat{D}$.
\hat{p}_{ij}	TL price (\$) currently charged by the carrier to demand in lane $(i, j) \in \widehat{D}$.
$G(N, A)$	Carrier's transportation network.
N	Set of pickup/delivery nodes operated by the carrier.
A	Set of arcs operated by the carrier $A = \bar{A} \cup \tilde{A}$.
\bar{A}	Subset of demand arcs associated to auctioned and current lanes $\bar{A} = D \cup \widehat{D} \subset A$.
\tilde{A}	Subset of repositioning arcs associated to empty movements $\tilde{A} \subset A$.
c_{ij}	Unitary cost per TL in a demand lane $(i, j) \in \bar{A}$. $c_{ij} = \bar{c}_{ij} + \kappa_i + \kappa_j$.

Notation	Definition
\bar{c}_{ij}	Unitary traversing (loaded) cost in lane carrying demand $(i, j) \in \bar{A}$.
κ_i, κ_j	Unitary loading/unloading costs associated to pickup $i \in N$ and delivery $j \in N$ nodes.
\tilde{c}_{ij}	Unitary traversing (empty) cost in each repositioning arc $(i, j) \in \tilde{A}$.
$\bar{\Pi}$	Carrier's profit threshold below which it is not willing to serve bundles.
Π_b	Total profit associated to bundle $b \in B$.
π_b	Unitary profit per TL in bundle $b \in B$.
Γ_b	Set of synergetic arcs used to give continuity to auctioned lanes β_b in bundle $b \in B$. $\Gamma_b \subset \hat{D} \cup \tilde{A}$.
x_{ij}^b	Flow in each arc (i, j) of auctioned lanes $\beta_b \subset D$ and synergic arcs $\Gamma_b \subset \hat{D} \cup \tilde{A}$ associated to bundle $b \in B$. Equivalent to max. bundle demand $x_b = x_{ij}^b, \forall (i, j) \in \beta_b \cup \Gamma_b, \forall b \in B$.
$\sigma_{ij}^{b\ell}$	Binary variable. $\sigma_{ij}^{b\ell} = 1$ if bundle b is part of the subset of bundles $\ell \in \mathcal{B}_{ij}$ covering the lane $(i, j) \in D$ such that current demand f_{ij} is satisfied, $\sigma_{ij}^{b\ell} = 0$ otherwise.
\mathcal{B}_{ij}	Set off mappings ℓ relating each demand arc $(i, j) \in D \cup \hat{D}$ with every possible combination of bundles covering it.
$\zeta_{ij}^{b\ell}$	Binary variable. $\zeta_{ij}^{b\ell} = 1$ if bundle b is part of the subset of bundles $\ell \in \mathcal{B}_{ij}$ covering the lane $(i, j) \in \hat{D}$ such that new auctioned demand q_{ij} is considered, $\zeta_{ij}^{b\ell} = 0$ otherwise.
N_b	Set of nodes considered in bundle $b \in B$. $N_b \subset N$.

This research addresses the perspective of a TL carrier invited to this auction. The challenge for this carrier is constructing bundles of lanes with the right combination of prices, lanes, and volumes. Defining competitive prices is important to make the bundle desirable to the shipper and, at the same time, profitable to the carrier. Profitability is obtained when these prices compensate bundle costs. Bundles have to be constructed such that each of them represents an expected profit higher than a profit threshold defined by the carrier. The main variable costs for carrier's operation are related to loaded and empty movements. Loaded-movement costs are determined by pickup costs, traversing

costs, and delivery costs. On the other hand, empty (uncharged) costs are incurred when trucks are repositioned between loaded lanes. Notice that only loaded movements produce revenues. Thus, the carrier can eliminate empty costs by properly combining follow-up (loaded) lanes. This is achieved either by combining lanes in the auction or mixing them with lanes currently served for other clients. Therefore, considering this current demand is critical in the construction of competitive bundles.

The problem is formally defined as follows. Let D indicate the set of lanes auctioned by the shipper. Each auctioned lane $(i, j) \in D$ is described by a pickup node i , a delivery node j , and volume of TL per unit of time required to be served by the shipper and denoted as q_{ij} . The reservation price (lane valuation or maximum price the shipper is willing to pay) for this lane is denoted as \bar{p}_{ij} . The group or set of bundles constructed by the specific carrier considered in this problem is represented by the notation B . Each bundle in this set is denoted as b . Following this idea, the set of lanes that compose a bundle $b \in B$ is denoted as $\beta_b \subset D$ (a subset of the auctioned lanes). The maximum volume that the shipper is willing to serve in each bundle is denoted as x_b . Finally, the price charged for each TL if the bundle is awarded is denoted as p_b . From the specific perspective of the carrier, let \widehat{D} denote the set of lanes currently served by the carrier. Each lane $(i, j) \in \widehat{D}$ is described by a pickup node i , a delivery node j , a known demand level denoted as f_{ij} , and a shipment price denoted by \hat{p}_{ij} . The bundling problem is considered from a network perspective which requires defining a network $G(N, A)$ composed by a set of nodes, denoted N , and a set of arcs, denoted A . The set of nodes N indicates the location of pickups and deliveries. The set of arcs A indicates connections

between nodes. There are two types of arcs: (1) loaded arcs from pickups to deliveries (subset \bar{A}), and (2) empty movements from deliveries to pickups (subset \tilde{A}), formally $A = \bar{A} \cup \tilde{A}$. The set of loaded arcs is basically formed by lanes, which can be auctioned D or current \hat{D} lanes, formally $\bar{A} = D \cup \hat{D}$. Each loaded movement, represented by an arc (i, j) in the set \bar{A} , is associated to a traversing cost denoted by \bar{c}_{ij} , a pickup cost κ_i , and a delivery cost κ_j . Then, the total cost associated to a TL movement over this arc is $c_{ij} = \bar{c}_{ij} + \kappa_i + \kappa_j$. On the other hand, the cost for each TL movement over a repositioning arc (i, j) in the set \tilde{A} is denoted as \tilde{c}_{ij} . The notation $\bar{\Pi}$ is used to indicate the profit threshold that determines whether a bundle is desirable by the carrier or not.

The problem to solve is stated as follows. Given the conditions presented above, a carrier is asked to analyze the set of existing D and new \hat{D} lanes to determine the best combination of bundles B to submit to the TL CA that increases its expected profits. This is formally represented by the MIQP formed by the Objective Function (4.1) that is subjects to Constraints (4.2) to (4.13).

There are four sets of variables in this problem: (i) x_b indicating the maximum amount of demand that the carrier is willing to serve if bundle $b \in B$ if awarded, (ii) p_b indicating the price per TL in the bundle b if awarded, (iii) binary variable $\sigma_{ij}^{b\ell} = 1$ if bundle b is part of the subset of bundles $\ell \in \mathcal{B}_{ij}$ covering the lane $(i, j) \in D$ such that current demand f_{ij} is satisfied, $\sigma_{ij}^{b\ell} = 0$ otherwise, and (iv) binary variable $\varsigma_{ij}^{b\ell} = 1$ if bundle b is part of the subset of bundles $\ell \in \mathcal{B}_{ij}$ covering the lane $(i, j) \in \hat{D}$ such that new auctioned demand q_{ij} is considered, $\varsigma_{ij}^{b\ell} = 0$ otherwise.

The Objective Function (4.1) maximizes the total profit of bundles submitted to the auction. Notice that in this formulation the set B has to consider all the possible combinations of bundle that can be constructed. This extremely problematic and is one of the main reasons supporting the development of the program introduced in the next section.

$$\max \sum_{b \in B} \Pi_b \quad (4.1)$$

The total profit associated to each bundle is denoted by Π_b and formally defined in Constraint (4.2) as the product between π_b and x_b , where π_b indicates the marginal profit for each TL served in bundle b , and x_b is a variable previously defined.

$$\Pi_b = \pi_b x_b, \forall b \in B \quad (4.2)$$

Each bundle is composed by a set of auctioned lanes β_b and a set of synergetic arcs denoted as Γ_b . These arcs are either lanes currently served by the carrier (in the set \widehat{D}), which remove empty trips connecting auctioned lanes (in β_b), or the arcs associated to empty repositioning (in the set \tilde{A}) if the latter is not possible. So, Γ_b is a subset of these arcs formally defined as $\Gamma_b \subset \widehat{D} \cup \tilde{A}$. This distinction is required to define π_b in Constraint (4.3) as the summation of the profit per truckload perceived by three types of arcs considered in each bundle: (i) profit for auctioned lanes in the bundle β_b (first bracket), (ii) profit perceived by synergetic lanes of current demand $\Gamma_b \cap \widehat{D}$ (second bracket), (iii) and costs of empty repositioning $\Gamma_b \cap \tilde{A}$ (third bracket).

$$\pi_b = \left(\sum_{(i,j) \in \beta_b} (p_b - c_{ij}) \right) + \left(\sum_{(i,j) \in \Gamma_b \cap \widehat{D}} \hat{p}_{ij} - c_{ij} \right) - \left(\sum_{(i,j) \in \Gamma_b \cap \tilde{A}} \tilde{c}_{ij} \right), \forall b \in B \quad (4.3)$$

Constraint (4.4) specifies that the total profits for every individual bundle Π_b has to be greater than or equal to the profit threshold $\bar{\Pi}$ defined by the carrier.

$$\bar{\Pi} \leq \Pi_b, \forall b \in B \quad (4.4)$$

Constraint (4.5) indicates that the price for each bundle p_b has to be at most the lowest reservation price \bar{p}_{ij} for lanes contained in such bundle. There are three important considerations behind this: (i) it is consistent with the concept of pricing for TL CA, (ii) although the lowest reservation price is the highest for at least one lane, it is less than or equal to the reservation prices in other lanes and, hence, more attractive, and (iii) Although cost-based pricing would be lower, it would be prejudicial for carrier profits leaving money on the table that the shipper would be willing to pay.

$$p_b \leq \bar{p}_{ij}, \forall (i,j) \in \beta_b, \forall b \in B \quad (4.5)$$

Constraint (4.6) indicates that the maximum flow x_b willing to be served in each bundle has to be assigned to each auctioned lane, i.e., $x_b = x_{ij}^b, \forall (i,j) \in \beta_b$, and synergetic arc, i.e., $x_b = x_{ij}^b, \forall (i,j) \in \Gamma_b$, in every bundle $b \in B$.

$$x_b = x_{ij}^b, \forall (i,j) \in \beta_b \cup \Gamma_b, \forall b \in B \quad (4.6)$$

Constraint (4.7) indicates that for every current lane $(i,j) \in \widehat{D}$, there exists at least a cover of bundles $\mathcal{b} \in \mathcal{B}_{ij}$ that satisfies its demand denoted by f_{ij} . This is required because current lanes served by the carrier (denoted by \widehat{D}) have to be served and for each bundle considering this synergetic lane there must exist complementary bundles that

guarantee serving all its demand. Variables $\sigma_{ij}^{b\ell}$ define such combinations that are exponentially in nature. This is part of the problem that is addressed by the methodology proposed below.

$$\sum_{b \in B} x_{ij}^b \sigma_{ij}^{b\ell} = f_{ij}, \forall \ell \in \mathcal{B}_{ij}, \forall (i, j) \in \widehat{D} \quad (4.7)$$

Consequently, Constraint (4.8) indicates that for every new auctioned lane $(i, j) \in D$ there might be bundles where demand q_{ij} is partially (or totally) covered. In this profit maximization approach, Constraint (4.8) prefers more profitable auctioned lanes and even leaves unserved those that are not attractive for the trucking firm. The same combinatorial problem presented for Constraint (4.7) occurs here.

$$\sum_{b \in B} x_{ij}^b \varsigma_{ij}^{b\ell} \leq q_{ij}, \forall \ell \in \mathcal{B}_{ij} \subset B, \forall (i, j) \in D \quad (4.8)$$

Constraint (4.9) gives flow conservation to every node $j \in N_b$, where N_b is the set of nodes covered by bundle $b \in B$.

$$\sum_{(i,j) \in \beta_b \cup \Gamma_b} x_{ij}^b = \sum_{(j,k) \in \beta_b \cup \Gamma_b} x_{jk}^b, \forall j \in N_b \subset N, \forall b \in B \quad (4.9)$$

Finally, constraints (4.10)-(4.13) properly define non-negative and binary variables in this problem.

$$x_b \geq 0, \forall b \in B \quad (4.10)$$

$$p_b \geq 0, \forall b \in B \quad (4.11)$$

$$\sigma_{ij}^{b\ell} \in \{0,1\}, \forall b \in B, \forall \ell \in \mathcal{B}_{ij} \subset B, \forall (i, j) \in \widehat{D} \quad (4.12)$$

$$\varsigma_{ij}^{b\ell} \in \{0,1\}, \forall b \in B, \forall \ell \in \mathcal{B}_{ij} \subset B, \forall (i, j) \in D \quad (4.13)$$

Song and Regan (2003, and 2005) and Lee et al. (2007) recognize the computational complexity of bidding advisory models for TL CA. The complete enumeration of bundles

grows exponentially with respect of the analyzed lanes. Furthermore, analyzing each bundle involves the solution of an NP-problem. This computational problem is aggravated by the quadratic expressions required to address pricing and demand segmentation in this research. Thus a solution procedure (BM◦T) is proposed to find a balance between good quality bundles and a computationally tractable approach. This method is presented in the following section.

4.3 Methodology

A bidding advisory model that incorporates pricing and demand segmentation in the context of TL CA is computationally complex. This section introduces BM◦T, a computational package that balances between good quality bundles and low computational burden.

Figure 4.1 describes the main algorithm behind BM◦T, which is intuitively described as follows. The program is initialized using the inputs described in the previous section. The main advantage of this approach is taking advantage of the special structure of the MIQP (4.1)-(4.13) to find bundles by iteratively solving minimum-cost flow (MCF) problems with polynomial solution time. Subsection 4.3.1 reviews the MCF problem and explains how the inputs of MIQP (4.1)-(4.13) are transformed into a MCF type of network. After solving a MCF problem, the resulting flows are explored in polynomial time by Tarjan's algorithm in order to construct bundles as shown in Subsection 4.3.2. If profits for these bundles are acceptable (higher than the carrier's threshold) and share the same price, bundles are generated and stored. Then an arc is removed from the network adding a perturbation to the next iteration. The proposed arc selection criterion (Subsection 4.3.3) iteratively removes arcs with high capacity utilization and low flow and centrality.

On the other hand, if profits are acceptable but prices are not the same, the network is modified duplicating and adjusting arcs so that the appropriate prices are available the next time the MCF problem is solved (Subsection 4.3.4). When the MCF solution returns a profit below the acceptable threshold, the last removed arc is added back to the problem and a new arc is removed. When all candidate arcs are removed, the process stops and returns the bundles. The following subsections provide specific details for each module.

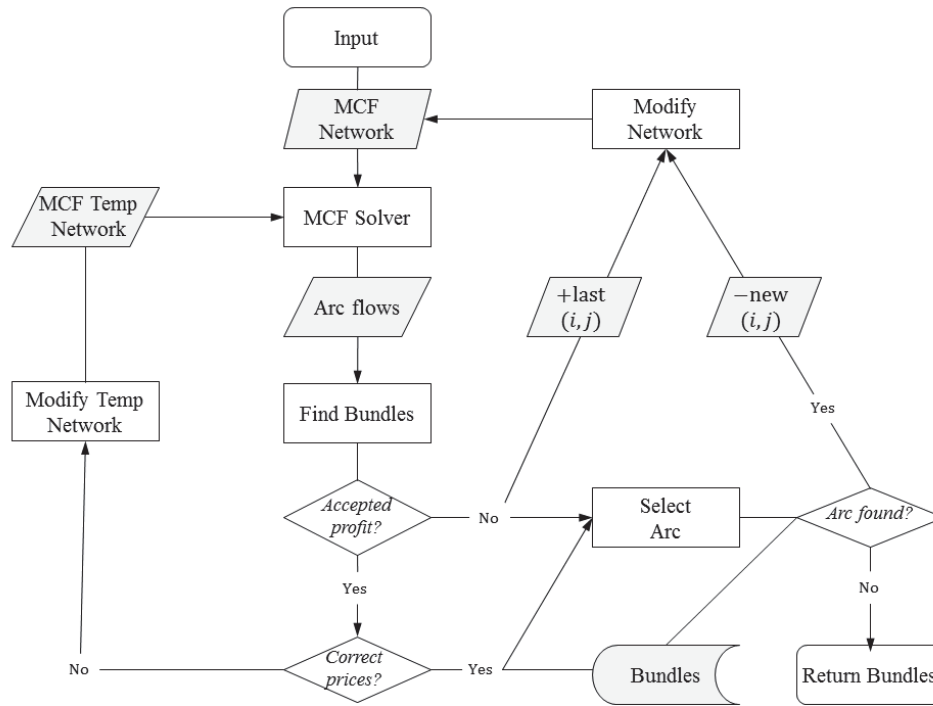


Figure 4.1 BM◦T: bidding model for TL demand

4.3.1 Minimum-cost flow (MCF) problem: special features for bundle construction

First, the MCF problem is reviewed based on the work by Ahuja et al. (1993). Then, it is related to the current bundling problem and integrated to the general framework. Specific notation used in this subsection is summarized in Table 4.2.

Table 4.2 Specific mathematical notation for the MCF problem

Notation	Definition
$G(\mathcal{N}, \mathcal{A})$	MCF type of network derived from $G(N, A)$.
\mathcal{N}	Set of nodes considered in the MCF problem. $\mathcal{N} = N \cup \mathcal{N}_1$.
\mathcal{N}_1	Set of dummy nodes added to N to transform $G(N, A)$ into $G(\mathcal{N}, \mathcal{A})$.
\mathcal{A}	Set of arcs considered in the MCF problem. $\mathcal{A} = D \cup \tilde{A} \cup \mathcal{A}_1$.
\mathcal{A}_1	Set of dummy arcs connected to dummy nodes $\hat{i} \in \mathcal{N}_1$ to transform $G(N, A)$ into $G(\mathcal{N}, \mathcal{A})$.
π_{ij}	Unitary cost (negative profit) to each arc $(i, j) \in \mathcal{A}$.
u_{ij}	Arc capacity for every arc $(i, j) \in \mathcal{A}$.
$f(i)$	Supply/demand associated to each node $i \in \mathcal{N}$.
x_{ij}	Arc flow for each arc $(i, j) \in \mathcal{A}$.
B'	Subset of bundles submitted to the auction $B' \subset B$.

Consider a directed network $G(\mathcal{N}, \mathcal{A})$ intended to transfer flow from supply to demand nodes. Each arc $(i, j) \in \mathcal{A}$ has traversing cost π_{ij} and capacity u_{ij} . Supply nodes input $f(i) > 0$ flow to the network and demand nodes require $f(i) < 0$ flow from it. For other nodes $f(i) = 0$. The MCF problem (4.14)-(4.16) finds the arc flows x_{ij} that minimize total system cost.

$$\min \sum_{(i,j) \in \mathcal{A}} \pi_{ij} x_{ij} \quad (4.14)$$

s.t.

$$\sum_{j \in \mathcal{N}} x_{ij} - \sum_{j \in \mathcal{N}} x_{ji} = f(i), \forall i \in \mathcal{N} \quad (4.15)$$

$$0 \leq x_{ij} \leq u_{ij}, \forall (i, j) \in \mathcal{A} \quad (4.16)$$

The objective function (4.14) minimizes total flow cost. Constraint (4.15) indicates flows conservation at every node. Constraint (4.16) specifies that arc flow cannot exceed arc capacity. The MCF problem requires all inputs $(\pi_{ij}, f(i), u_{ij})$ to be integral, supply

demand balance, i.e. $\sum_{i \in N} f(i) = 0$, and non-negative arc costs. Notice, however, that the last requirement imposes no loss of generality and can be relaxed, e.g., using arc reversal transformations.

There are several algorithms that solve the MCF problem in polynomial time. Király and Kovács (2012) summarize many of them (Table 4.3).

Table 4.3 MCF Algorithms and worst case running time (Király and Kovács, 2012)

Algorithm	Worst case running time	Reference
Cycle-canceling	$O(N A ^2CU)$	Klein (1967)
Minimum-mean cycle-canceling	$O(N ^2 A ^2 \min\{\log(N C), A \log(N)\})$	Goldberg and Tarjan (1989)
Cancel-and-tighten	$O(N ^2 A \min\{\log(N C), A \log(N)\})$	Goldberg and Tarjan (1989)
Successive shortest path	$O(N U * SP_+(N , A))$	Iri (1960), Jewell (1958), Busacker and Gowen (1960), Edmonds and Karp (1972), Tomizawa (1971)
Capacity-scaling	$O(A \log(U) * SP_+(N , A))$	Edmonds and Karp (1972), Orlin (1993)
Cost-scaling	$O(N ^2 A \log(N C))$	Goldberg and Tarjan (1989) Röck (1980), Bland and Jensen (1992)
Network simplex	$O(N A ^2CU)$	Ahuja et al. (1995), Dantzig (1998), Kelly and O'Neill (1991)

Where, highest cost $C = \max(c_{ij})$, highest capacity $U = \max(u_{ij})$, $SP_+(n, m) = O((n + m)\log(n))$ for Dijkstra's algorithm with binary heaps

Framing the bundling problem in the MCF problem context is important to take advantage of its computational efficiencies. Interestingly, there are similarities between these two problems. The flows associated to the optimal bid that the carrier can submit to the auction with bundle-independent prices, akin to (Lee et al. 2007), can be obtained solving the MCF problem (4.14)-(4.16) with the following network transformations (Figure 4.2 (a)(b) illustrates Steps 1.1-1.7).

For every current-demand lane $(i, j) \in \widehat{D}$:

Step 1.1. Create dummy node $\hat{i} \in \mathcal{N}_1$, where \mathcal{N}_1 is the set of such nodes.

Step 1.2. Create dummy arc $(i, \hat{i}) \in \mathcal{A}_1$ connecting the tail of $(i, j) \in \widehat{D}$ to $\hat{i} \in \mathcal{N}_1$, where \mathcal{A}_1 is the set of such arcs.

Step 1.3. Set dummy arc cost $\pi_{i\hat{i}} = \hat{p}_{ij} - c_{ij}$ and capacity $u_{i\hat{i}} = f_{ij}$

Step 1.4. Associate \hat{i} with demand $f(\hat{i}) = -f_{ij}$ and j with supply $f(j) = f_{ij}$

Step 1.5. Temporally remove $(i, j) \in \widehat{D}$ from the MCF problem.

For every new-auctioned lane $(r, s) \in D$:

Step 1.6. Set arc cost $\pi_{rs} = c_{rs} - \bar{p}_{rs}$ and capacity $u_{rs} = q_{rs}$

Step 1.7. Associate no demand/supply to r, s , i.e., $f(r) = f(s) = 0$

Additionally, for every repositioning arc $(o, d) \in \tilde{A}$:

Step 1.8. Set arc cost to the repositioning cost $\pi_{od} = \tilde{c}_{od}$

Step 1.9. Set arc capacity to the associated lowest adjacent one, i.e., if $(\cdot, o) \in \widehat{D} \rightarrow u_{od} = \min\{f(\cdot), u_{d(\cdot)}\}$, else $u_{od} = \min\{u_{(\cdot)o}, u_{d(\cdot)}\}$

The MCF network $G(\mathcal{N}, \mathcal{A})$ is composed by the sets of arcs $\mathcal{A} = D \cup \tilde{A} \cup \mathcal{A}_1$ and nodes $\mathcal{N} = N \cup \mathcal{N}_1$.

Notice that, when lane price is higher than arc cost, this transformation involves negative cost arcs $\pi_{ij} < 0$. Minimizing costs in a network with these characteristics is equivalent to maximizing profits (negative arcs are not a problem for MCF algorithms as mentioned before).

This transformation is used to find an optimal set of flows x_{ij} in which all current demand is served \widehat{D} and new auctioned lanes D are served only if they maximize profits (minimize modified costs). So it is equivalent to finding an optimal combination of potential bundles $B' \subset B$ associated to a mapping $\ell \in \mathcal{B}_{ij}$ where constraints (4.7)-(4.8) hold $\forall (i, j) \in D \cup \widehat{D}$. However, it is not possible to distinguish the specific flows x_{ij}^b associated to each bundle $b \in B'$ because they are aggregated, i.e., $x_{ij} = \sum_{b \in B'} (x_{ij}^b)$, $\forall (i, j) \in A$. The following subsection explains the steps to disaggregate them and uncover the associated set of bundles B' .

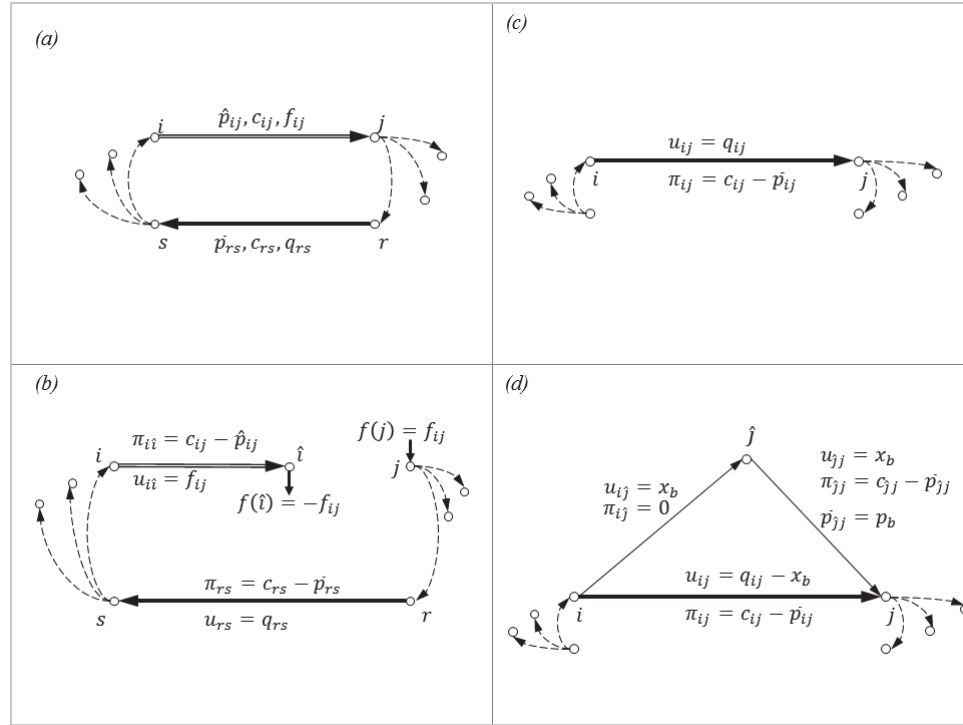


Figure 4.2 Network transformations from original (a) to MCF problem (b), and price/capacity modification from MCF network (c) to MCF temporal network (d).

4.3.2 Finding bundles from aggregated flows

After solving the MCF problem the resulting optimal arc flows x_{ij} are aggregated in an optimal partition that serves current demand and includes new lanes that maximize system profits. However, it is not clear what lanes are bundled together. Then, a disaggregating method is required. The objective of this method is finding tours of tuck flow that are subsequently used to generate bundles. Specific notation used in this subsection is summarized in Table 4.4.

Table 4.4 Specific mathematical notation to find bundles from aggregated flows

Notation	Definition
N_k	k^{th} subset of strongly connected (SC) nodes in a graph $G(N, A)$. $N_k \subset N: \cup_k \{N_k\} = N$.
t_b^k	Set of arcs forming a tour associated to bundle $b \in B$ obtained from the SC set N_k .
p_{ij}^b	Price for every arc $(i, j) \in t_b^k$.

Notation	Definition
δ	Binary indicator. $\delta = 0$ if there exists a bundle with unacceptable profit, $\delta = 1$ otherwise.
ρ	Binary indicator. $\rho = 0$ if there exists a bundle with inconsistent prices, $\rho = 1$ otherwise.
B_1	Set of potential bundles related to tours with same prices $B_1 = \{b: p_{ij}^b = p_b, \forall (i, j) \in \beta_b\}$.
B_2	Set of hypothetical bundles related to tours with different prices $B_2 = \{b: \exists (h, i), (j, k) \in \beta_b, p_{hi}^b \neq p_{jk}^b\}$.

Tarjan (1972) proposes an efficient algorithm $O(mn)$ to find subsets $N_k \subset N: \cup_k \{N_k\} = N$ of strongly connected (SC) components in a directed graph. The special characteristic of a SC set N_k is that for each pair of nodes $i \in N_k, j \in N_k$ there exist paths $i \Rightarrow j$ and $j \Rightarrow i$, i.e., a round tour b starting from any node i passing by any other node j traversing the set of arcs t_b^k . The recursive depth-first search used by Tarjan's algorithm to find every N_k is also used to obtain the corresponding tours $\{t_b^k\}$. Having each t_b^k is important to collect flow x_b and corresponding prices $p_{ij}^b, \forall (i, j) \in t_b^k$. This information will determine whether t_b^k is considered to generate a bundle $b \in B'$ or not. Binary indicators $\delta, \rho \in \{0, 1\}$ identify the existence of unacceptable-profit bundles ($\delta = 0$) and inconsistent prices in a bundle ($\rho = 0$), $\delta = 1, \rho = 1$ otherwise.

The method to find bundles from aggregated flows is summarized as follows:

Step 2.1: Associate flow/cost $x_{ij} \forall (i, j) \in \mathcal{A}_1$ with corresponding $x_{ij} \forall (i, j) \in A$

Step 2.2: Temporally remove each $(i, j) \in A$ such that $x_{ij} = 0$

Step 2.3: Use Tarjan's algorithm over $G(N, A)$ to find SC components N_k and underlying tours t_b^k

Step 2.4: For each k, b pair:

Step 2.4.1: Compute tour flow $x_b = \min\{x_{ij}: (i, j) \in t_b^k\}$

Step 2.4.2: Segregate arcs into auctioned lanes $\beta_b = t_b^k \cap D$ and s lanes $\Gamma_b = t_b^k \setminus \beta_b$

Step 2.4.3: Collect tour prices for new auctioned lanes $\{p_{ij}^b: (i, j) \in \beta_b\}$

Step 2.4.4: Compute tour profits $\Pi_b = x_b \sum_{(i,j) \in \beta_b \cup \Gamma_b} \pi_{ij}$

Step 2.5: If there exists an unacceptable profit, i.e., $\exists \Pi_b: \Pi_b < \bar{\Pi}$, set $\delta = 0$, else $\delta = 1$.

Step 2.6: If $\delta = 1$ do the following: if all prices $\{p_{ij}^b\}$ for new auctioned lanes in the tour are the same, i.e., $p_{ij}^b = p_{rs}^b, \forall (i, j), (r, s) \in \beta_b$, then add tour b to the set of bundles $B_1 = B_1 \cup \{b\}$, else add b to the set for next network modifications $B_2 = B_2 \cup \{b\}$.

Step 2.7: If the set B_2 is empty, then set $\rho = 1$, set $B' = B_1$ and store B' with other already found bundles $B = B \cup B'$, else $\rho = 0$

Valuable information is obtained after running this module. If there are tours that result in bundles with unacceptable profits, i.e., $\delta = 0$, the current MCF solution is not considered. This implies adding back the last removed arc and removing a new one as will be explained in Subsection 4.3.3.

On the other hand, i.e., $\delta = 1$, tours are segregated into potential bundles B_1 , i.e., tours where all new auctioned demand share the same prices, and those that need to be revised with respect to price B_2 , i.e., tours with different prices. If all prices are right, i.e., $B_2 = \emptyset$ then a new arc is removed from the network, as will be explained in Subsection 4.3.3, and bundles with correct prices are added to the global solution. Otherwise, the network is modified so that the corresponding flows have the option to obtain the same prices. This will be explained in Subsection 4.3.4.

4.3.3 Finding bundles from aggregated flows

The MCF problem solution outputs an optimal set of flows that maximizes profits while satisfying demand-related and flow-conservation constraints. If all prices are correct, this solution can be used to generate a set of optimal bundles $B' \subset B$. However, there is high risk if only optimal bundles are submitted to the auction. If competitors have better prices for lanes in any of these bundles, the carrier will likely lose those lanes, which implies also losing all lanes in the corresponding bundles. Hence, a method to explore other good bundles is required. Specific notation used in this subsection is summarized in Table 4.5.

Table 4.5 Specific mathematical notation to modify the original network

Notation	Definition
BC_{ij}	Arc betweenness centrality for arc $(i, j) \in A$.
φ_{rs}^{ij}	Binary indicator. $\varphi_{rs}^{ij} = 1$ if arc $(i, j) \in A$ is traversed in the shortest path from $r \in N$ to $s \in N$, $\varphi_{rs}^{ij} = 0$ otherwise.
$\lambda_{ij} = 1$	Binary indicator. $\lambda_{ij} = 1$ if arc $(i, j) \in A$ has been removed from the network, $\lambda_{ij} = 0$ otherwise.
r_{ij}	Capacity usage ratio. $r_{ij} = x_{ij}/u_{ij}$, $\forall (i, j) \in A$.
y_{ij}	flow centrality criterion $y_{ij} = x_{ij} * BC_{ij}$, $\forall (i, j) \in A$.

But, how to find another set of flows that can produce different bundles at the same optimal MCF profit or within a narrow gap from it? Network perturbations are used to achieve this goal. This requires defining proper perturbation criteria that consider used arcs, unused capacity, and some metric of attractiveness. Perturbing very attractive arcs is not desirable because they are usually overlapped by several bundles to compensate low

attractiveness of other lanes. So, a criterion where perturbation goes from less to more desirable arcs is envisioned.

Another important question is how to account for network effects? This is important because an isolated arc can be unattractive but very relevant when jointly analyzed with other lanes. In this sense, a metric considering the importance or centrality of the arcs is required.

Betweenness Centrality (Anthonisse 1972, Freeman 1977, Newman 2010) is used to identify important central nodes/arcs in a network by counting the number of times these elements are used as bridges in the shortest paths between every node duplet. So, arc betweenness centrality is used as part of the selection criteria to perturb the network. Worst case running time for its computation is $O(n^3)$. It is performed once at the beginning of the algorithm when the original network $G(N, A)$ has not been perturbed. Arc betweenness centrality BC_{ij} is defined in Equation (4.17), where the binary variable $\varphi_{rs}^{ij} = 1$ if arc $(i, j) \in A$ is traversed in the shortest path from $r \in N$ to $s \in N$, $\varphi_{rs}^{ij} = 0$ otherwise.

$$BC_{ij} = \sum_{(r,s) \in A} \varphi_{rs}^{ij} \quad (4.17)$$

When bundles with correct prices are found, i.e., $p_b = p_{ij}^b \forall (i, j) \in \beta_b$ and $\rho = 1$, the current set of bundles is stored first, i.e., $B = B \cup B'$. Then, the following perturbation procedure is applied to remove an arc from the network. Let the binary indicator $\lambda_{ij} = 1$ designate that the arc (i, j) has been removed from the network, and $\lambda_{ij} = 0$ designate the contrary. For each arc $(i, j) \in A$ such that arc is used, i.e., $x_{ij} > 0$, it is not a current

demand arc, i.e., $(i, j) \notin \widehat{D}$, it is not connected to a current demand arc, i.e., $(\cdot, i), (j, \cdot) \notin \widehat{D}$, and it has not been removed before, i.e., $\lambda_{ij} = 0$.

Step 3.1: Compute capacity usage ratio $r_{ij} = x_{ij}/u_{ij} \in (0,1]$

Step 3.2: Compute flow centrality criterion $y_{ij} = x_{ij} * BC_{ij}$

Step 3.3: Select $(i, j) \in A$ such that $r_{ij} = \max\{r_{ij}\}$ and $y_{ij} = \min\{y_{ij}\}$

Step 3.4: Remove (i, j) from the network, $A = A \setminus \{(i, j)\}$, $\lambda_{ij} = 1$, i.e., $-\text{new}(i, j)$

(Figure 4.1)

The perturbation procedure prioritizes arc selection based on the following three concepts: (1) zero or small unused capacity, i.e., $\max\{r_{ij}\}$, (2) low flow, and (3) low centrality (periphery), i.e., $\min\{y_{ij}\}$. Concept (1) gives flexibility to use such capacity in later iterations. (2) and (3) protect important arcs that can overlap in several bundles. The selected arc is removed from the network and not considered in next iterations.

The overall algorithm stops when it is not possible to select an arc to remove. Notice that arcs related to current demand are maintained in the network. This guarantees that new auctioned lanes in the resulting bundles either have synergies with the current lanes or do not affect their current operation.

The possibility of removing arcs resulting in bundles with unacceptable profits exists, i.e., $\delta = 1$ (Subsection 4.3.2). When this happens, the last removed arc (i, j) is added back to $G(N, A)$, i.e., $A = A \cup \{(i, j)\}$, $+\text{last}(i, j)$ (Figure 4.1), removal criteria are estimated again and a new arc is selected. Notice that $\lambda_{ij} = 1$ remains and this arc is not part of the removal choice set.

4.3.4 Temporal Network

Subsection 4.3.2 shows how to find potential bundles where all new auctioned lanes have the same price B_1 . However, it is also possible to find tours where prices are not the same B_2 , so bundles cannot be generated. This subsection presents an iterative procedure to handle this case by considering the hypothetical case in which tours in B_2 are used as bundles. Specific notation used in this subsection is summarized in Table 4.6.

Table 4.6 Specific mathematical notation to define the temporal network

Notation	Definition
$G'(\mathcal{N}', \mathcal{A}')$	Temporal MCF type of network derived from $G(\mathcal{N}, \mathcal{A})$.
\mathcal{N}'	Set of temporal nodes considered in temporal MCF problems. $\mathcal{N}' = \mathcal{N} \cup \mathcal{N}'_1$.
\mathcal{N}'_1	Set of dummy nodes added to \mathcal{N} to transform $G(\mathcal{N}, \mathcal{A})$ into $G'(\mathcal{N}', \mathcal{A}')$.
\mathcal{A}'	Set of temporal arcs considered in the temporal MCF problem. $\mathcal{A}' = \mathcal{A} \cup \mathcal{A}'_1$.
\mathcal{A}'_1	Set of dummy arcs connecting dummy nodes $\hat{j} \in \mathcal{N}'_1$ to transform $G(\mathcal{N}, \mathcal{A})$ into $G'(\mathcal{N}', \mathcal{A}')$.
H	History tracker. Stores B_1 and B_2 explored in previous iterations over $G'(\mathcal{N}', \mathcal{A}')$.
Π^*	Best profit for bundles in H .
B^*	Bundle associated to the best profit Π^* from H .
$ID(\cdot)$	Unique identification for the bundle setup $(\cdot) = B_1 \cup B_2$.

Let $p_b = \min\{\hat{p}_{ij}: (i, j) \in \beta_b, b \in B_2\}$ be the hypothetical price for each $b \in B_2$ if it was submitted to the auction. The lowest price is selected because otherwise it violates the maximum value (reservation price) the shipper is willing to pay for one or more lanes in the bundle (i.e., from a rational deterministic perspective the bundle would never be selected). Likewise, relate $b \in B_2$ with the hypothetical flow x_b (also available from

Subsection 4.3.2). A temporal network is generated following the procedure below (Figure 4.2 (c)(d) illustrates Steps 4.3-4.6):

Step 4.1. Create a copy of the MCF network, i.e., MCF Temporal Network

$$G'(\mathcal{N}', \mathcal{A}') = G(\mathcal{N}, \mathcal{A})$$

Step 4.2. Reduce capacities for arcs related to potential bundles in B_1 , i.e., $u_{ij} =$

$$u_{ij} - x_b, \forall (i, j) \in \beta_b \cup \Gamma_b, \forall b \in B_1$$

Step 4.3. Create a node \hat{j} for every new auctioned lane in the set of hypothetical

bundles B_2 if price is inconsistent with the computed hypothetical price, i.e., $\mathcal{N}'_1 = \mathcal{N}'_1 \cup \{\hat{j}\}, \forall (i, j) \in \beta_b, \forall b \in B_2: p_b \neq \bar{p}_{ij}$, and add them to the copied set of nodes $\mathcal{N}' = \mathcal{N}' \cup \mathcal{N}'_1$.

Step 4.4. Create two arcs connecting this node. One from the tail i of (i, j) , i.e.,

$\mathcal{A}'_1 = \mathcal{A}'_1 \cup \{(i, \hat{j})\}$, and another to the head j of (i, j) , i.e., $\mathcal{A}'_1 = \mathcal{A}'_1 \cup \{(\hat{j}, j)\}$. Add them to the copied set of arcs $\mathcal{A}' = \mathcal{A}' \cup \mathcal{A}'_1$.

Step 4.5. For arc (i, \hat{j}) , set capacity to the hypothetical bundle flow $u_{ij} = x_b$ and cost

to zero $\pi_{ij} = 0$

Step 4.6. For arc (\hat{j}, j) , set capacity to the hypothetical bundle flow $u_{jj} = x_b$, and

update price and cost based on the current hypothetical price, i.e., $\bar{p}_{jj} = p_b$, $\pi_{jj} = c_{jj} - \bar{p}_{jj}$

Notice that it is possible to enter this module with a $G'(\mathcal{N}', \mathcal{A}')$ if prices are not consistent after the last modification of $G(\mathcal{N}, \mathcal{A})$ (or even last version of $G'(\mathcal{N}', \mathcal{A}')$). In this case, the generation of new arcs has to properly reduce/increase capacity to temporal arcs already priced or create new if corresponding prices have not been considered.

There are special considerations for the process that updates $G'(\mathcal{N}', \mathcal{A}')$. It stops when bundles/tours with unacceptable profits are found. Notice that the unacceptable profit for a tour with different prices $b \in B_2$ is an upper bound to the corresponding hypothetical bundle (all prices equal to the lowest one). So there is no loss of generality by stopping under this situation. When profits are acceptable but prices are not correct, there exists the possibility for the algorithm to flip-flop between pricing setups.

The following strategy is proposed to avoid this behavior and applied when accepted profits ($\delta = 1$) and incorrect prices ($\rho = 0$) are found. It requires a history tracker H that saves the identification of explored tours/bundles and updating the best bundle setup $\{\Pi^*, B^*\}$ at each iteration:

Step 4.7. Compute total profits for potential bundles $\Pi_1 = \sum_{b \in B_1} \Pi_b$

Step 4.8 Compute total profits for hypothetical bundles (assuming same prices)

$$\Pi_2 = \sum_{b \in B_2} \Pi_b$$

Step 4.9 Compute total profit $\Pi_1 + \Pi_2$ for current bundle setup $B_1 \cup B_2$.

Step 4.10 If $\Pi^* < \Pi_1 + \Pi_2$ then update current best setup $\Pi^* = \Pi_1 + \Pi_2, B^* = B_1 \cup B_2$

Step 4.11 Give a unique identification to this setup $ID(B_1 \cup B_2)$

Step 4.12 If the setup was not explored in the past, i.e., $\{ID(B_1 \cup B_2)\} \cap H = \emptyset$, store it in the history tracker, i.e., $H = H \cup \{ID(B_1 \cup B_2)\}$

Step 4.13 Else, i.e., the setup was explored in the past, let $B_1 = B^*$ and $B_2 = \emptyset$, and go to “Accepted profit” checking (Figure 4.1 after *Find bundles*, Step 2.5 Subsection

4.3.2), clean MCF temporal network $G'\{\mathcal{N}', \mathcal{A}'\}$ and continue working over the original MCF network $G(\mathcal{N}, \mathcal{A})$.

In this sense, when the algorithm finds a setup already explored, it stops and returns the current more profitable combination of potential and hypothetical bundles B^* , which will be stored in the set of bundles if they pass the “Accepted profit” test for individual bundles.

4.4 Numerical example

This section presents a numerical example illustrating the proposed bidding advisory model. The algorithm is coded in C++. Király and Kovács (2012) test the computational efficiency of different MCF software packages and algorithms. They find the C++ Library for Efficient Modeling and Optimization in Networks (LEMON) (Dezső et al. 2011) and its Network Simplex algorithm to be one of the most competent for large scale networks. Therefore, these modules are integrated to the framework. LEMON is developed by the Computational Infrastructure for Operations Research (COIN-OR) and also used for network manipulation. Other modules are developed by the authors. Experiments are run in a desktop with the following characteristics: Processor Intel® Core™2 Duo CPU E8400 @ 3.00GHz, Installed memory (RAM) 4.00GB.

Consider a carrier currently operating shipments $\hat{D} = \{(0,1), (2,3)\}$ associated to $f_{0,1} = 100$ and $f_{2,3} = 200$ TL per month and prices $p_{0,1} = \$5$ and $p_{2,3} = \$4$ respectively. The carrier operates over the region described by the grid network in Figure 4.3. Without loss of generality, assume that cost (loaded/unloaded) is such that $c_{ij} = 1$ for every arc in the grid network. The carrier participates of a TL CA where the set of

lanes $D = \{(4,5), (6,7), (8,9), (10,11)\}$ is auctioned with volumes $q_{4,5} = 200$, $q_{6,7} = 100$, $q_{8,9} = 500$, $q_{10,11} = 700$ TL per month, and reservation prices $\bar{p}_{4,5} = \$4$, $\bar{p}_{6,7} = \$5$, $\bar{p}_{8,9} = \$20$, $\bar{p}_{10,11} = \$20$ respectively. Carrier's acceptable profit is $\bar{\Pi} = 0$ for any bundle.

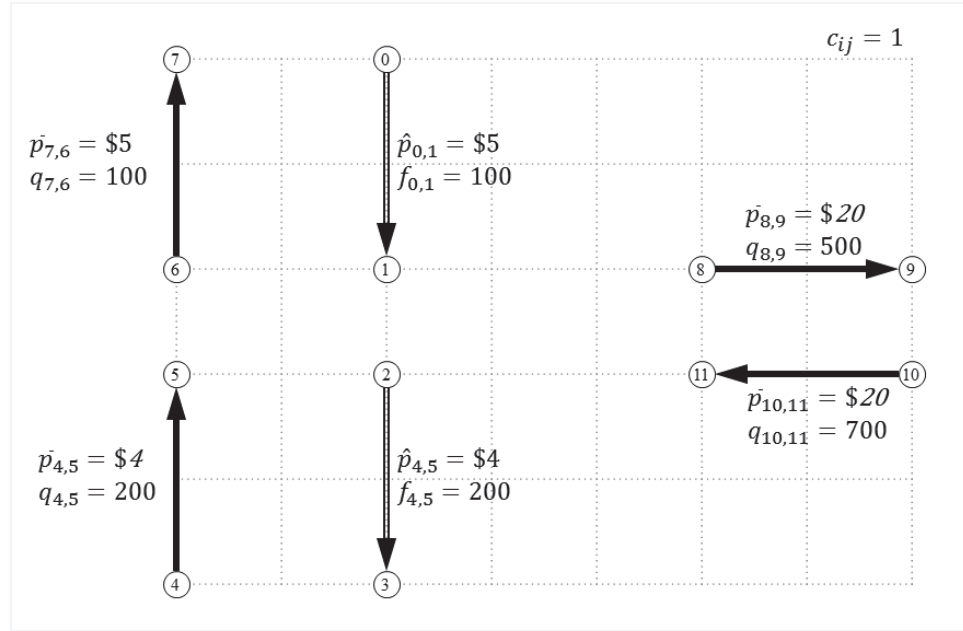


Figure 4.3 Numerical example

Table 4.7 Numerical Results

Bundle	Max Flow	Price	New lanes	Synergetic lanes	Profit	Π_b	Times
b	x_b	p_b	β_b	$\Gamma_b \cap \hat{D}$	Π_b	$/x_b$	found
0	500	20	$\{(8,9), (10,11)\}$	\emptyset	17000	34	5
1	700	20	$\{(10,11)\}$	\emptyset	11200	16	1
2	500	20	$\{(8,9)\}$	\emptyset	8000	16	1
3	200	20	$\{(10,11)\}$	\emptyset	3200	16	5
4	100	20	$\{(10,11)\}$	\emptyset	1600	16	5
5	100	4	$\{(4,5), (6,7)\}$	$\{(0,1), (2,3)\}$	500	5	1
6	200	4	$\{(4,5)\}$	$\{(2,3)\}$	400	2	3

7	100	5	$\{(6,7)\}$	$\{(0,1)\}$	400	4	1
7	100	5	$\{(6,7)\}$	$\{(0,1),(2,3)\}$	200	2	1
7	100	5	$\{(6,7)\}$	\emptyset	100	1	1

Table 4.7 presents the numerical results for this example. Computation time is 0.86 seconds. The bundle with highest expected profit is $b = 0$ achieved when $x_0 = 500$ TL per month are assigned. Interestingly, this bundle has the highest marginal profit $\Pi_0/x_0 = \$34/(\text{TL per month})$ which makes sense considering the economies of scope between lanes (8,9) and (10,11), i.e., serving (8,9) and (10,11) together is more beneficial than serving them separately. Although this bundles serves up to 500 TL per month, the model gives flexibility to consider the remaining 200 TL per month in bundle $b = 1$ which covers up to 700 TL per month on lane (10,11). Furthermore, bundles $b = 1,3,4$ can be aggregated into just one bundle ($b = 1$) given that they cover the same lanes, at the same prices with the same marginal profits. This is an artifact of the results that imposes no restriction and can be easily detected. Another example of economies of scopes and the benefits of this model is observed in bundle $b = 7$. Although it can be submitted to the auction alone and priced at $p_7 = \$5$ with maximum desired flow $x_6 = 100$, there are three possible scenarios that would determine the actual profit of the bundle: (1) serving it alone (backhaul type of operation) with profit \$100, (2) combining it with lanes (0,1), (2,3) with profit \$200, or (3) combining it with lane (0,1) with profit \$400. Notice that this is private carrier information hidden to the shipper. Furthermore, lane (6,7) is part of two bundles $b = 5,7$ with different prices, i.e., $p_5 = \$4$ and $p_7 = \$5$. This is possible because $b = 5$ bundles lanes (6,7) with (4,5) -public information-,

(0,1), and (2,3) -private carrier information-. The low price is attractive to the shipper and the marginal profit $\Pi_5/x_5 = \$5/(\text{TL per month})$ is better for the carrier than considering lanes (6,7) and (4,5) in isolation, i.e., $\Pi_7/x_7 = \$4/(\text{TL per month})$ in the best case and $\Pi_6/x_6 = \$2/(\text{TL per month})$ respectively. Finally, although a complete enumeration would find more combinations of bundles, the proposed method focusses on those that are more attractive without investing valuable computational resources in the less attractive ones, e.g., $\{\beta_{(\cdot)} = (4,5), x_{(\cdot)} = 200, p_{(\cdot)} = \$4\}$ with profit $\Pi_{(\cdot)} = 0$ would be present in a complete enumeration procedure but not considered here for its low profit and synergy with other lanes.

4.5 Conclusions

This research investigates the bidding problem faced by carriers participating in truckload (TL) combinatorial auctions (CA). Previous literature is improved by the following two contributions: (1) explicitly handling bundle generation and pricing, (2) determining the amount of flow willing to serve in each bundle. The former is relevant as value-based pricing has shown to be a meaningful strategy for revenue management, and the latter is important as CA in last years have require demand segmentation.

Given the enormous complexity of enumerating all possible bundles required to find an optimal solution to the bidding problem, a method is proposed to mine valuable bundles at a tractable computational time. This is important and meaningful for trucking analysts that require evaluating networks with hundreds of lanes in a TL CA setting.

CHAPTER 5. PRICING AND BUNDLING TRUCKLOAD SERVICES WITH STOCHASTIC DEMAND

5.1 Introduction

This chapter presents BM \circ TS, a model for bundling model for truckload (TL) operations that accounts for stochastic demand. Motivated by the gaps in literature (Subsection 1.2.3), This model contributes to previous research by (1) using a value-based pricing approach that properly handle the pricing rules of TL combinatorial auctions (CAs), (2) segmenting demand such that the carrier can specify the maximum volume of TLs willing to serve in each bundle, and (3) incorporating demand uncertainty. A two-stage minimum-cost flow (MCF) problem is embedded into BM \circ TS and solved using its deterministic equivalent (DE), which is formulated through network transformation and solved with efficient MCF algorithms, e.g., network simplex. The resulting aggregated flows, optimized for uncertain demand, are explored with a novel network algorithm that searches tours while constructing bundles. A numerical experiment illustrates the application of BM \circ TS.

The organization of the chapter is as follows. The problem addressed is introduced and motivated in Section 5.1. Then, it is clearly defined in Section 5.2. The methodology proposed to solve it (BM \circ TS) is presented in Section 5.3. Numerical examples demonstrate the application of BM \circ TS in Section 5.4. Finally, conclusions are provided in Section 5.5.

5.2 Problem definition and notation

This section introduces the mathematical notation used throughout the Chapter (Table 5.1), clearly defines the problem to solve, and formulates it as a stochastic mixed integer quadratic program (MIQP).

The problem is clearly defined as follows. Consider a TL CA organized by a shipper who requires transportation for a set of lanes D . Each auctioned lane $(i, j) \in D$ is associated to a number of truckloads per unit of time $q_{ij}(\omega)$ between a pickup origin i and a delivery destination j for the demand realization scenario $\omega \in \Omega$, where Ω is the set of demand realization scenarios. Each demand scenario is associated to a realization probability p_{ij}^ω . The shipper has a reservation price p_{ij} for each auctioned lane. Each carrier invited to the auction is asked to submit a set of desirable bundles B based on this information. A bundle $b \in B$ is related to the triplet $\{\beta_b, x_b, p_b\}$, where $\beta_b \subset D$ is the subset of auctioned lanes desired to serve, x_b is the maximum amount of demand desired by the carrier, and p_b is the price charged for each TL in b if it is assigned to the carrier.

Table 5.1 General mathematical notation in appearance order

Notation	Definition
D	Set of lanes auctioned in the TL CA. Each lane $(i, j) \in D$ associated to demand $q_{ij}(\omega)$, $\forall \omega \in \Omega$ and reservation TL price p_{ij} .
$q_{ij}(\omega)$	Demand realization of TL per unit of time associated to the scenario $\omega \in \Omega$ and auctioned lane $(i, j) \in D$.
Ω	Sorted set of scenarios for different realizations of demand
p_{ij}^ω	Demand realization probability for lane $(i, j) \in \bar{A}$ in scenario $\omega \in \Omega$
p_{ij}	Reservation TL price (\$) for to the auctioned lane $(i, j) \in D$.
B	Set of bundles submitted by a carrier to the auction. Each bundle $b \in B$ associated to the triplet $\{\beta_b, x_b, p_b\}$.
β_b	Set of auctioned lanes included in bundle $b \in B$. $\beta_b \subset D$.

Notation	Definition
x_b	Maximum amount of demand (TL per unit of time) that the carrier is willing to serve on each lane $(i, j) \in \beta_b$ in bundle $b \in B$.
p_b	Price the carrier would charge for every TL in bundle $b \in B$ if awarded by the shipper. $p_b \leq \bar{p}_{ij} \forall (i, j) \in \beta_b$.
\hat{D}	Set of lanes currently served by the carrier. Each lane $(i, j) \in \hat{D}$ associated to demand $f_{ij}(\omega)$, $\forall \omega \in \Omega$ and a current TL price \hat{p}_{ij} .
$f_{ij}(\omega)$	Demand of TL per unit of time currently served by the carrier in the lane $(i, j) \in \hat{D}$ associated to the scenario $\omega \in \Omega$.
\hat{p}_{ij}	TL price (\$) currently charged by the carrier to demand in lane $(i, j) \in \hat{D}$.
$G(N, A)$	Carrier's transportation network.
N	Set of pickup/delivery nodes operated by the carrier.
A	Set of arcs operated by the carrier $A = \bar{A} \cup \tilde{A}$.
\bar{A}	Subset of demand arcs associated to auctioned and current lanes $\bar{A} = D \cup \hat{D} \subset A$.
\tilde{A}	Subset of repositioning arcs associated to empty movements $\tilde{A} \subset A$.
c_{ij}	Unitary cost per TL in a demand lane $(i, j) \in \bar{A}$. $c_{ij} = \bar{c}_{ij} + \kappa_i + \kappa_j$.
\bar{c}_{ij}	Unitary traversing (loaded) cost in lane carrying demand $(i, j) \in \bar{A}$.
κ_i, κ_j	Unitary loading/unloading costs associated to pickup $i \in N$ and delivery $j \in N$ nodes.
\tilde{c}_{ij}	Unitary traversing (empty) cost in each repositioning arc $(i, j) \in \tilde{A}$.
$\bar{\Pi}$	Carrier's profit threshold below which it is not willing to serve bundles.
$y_b(\omega)$	Loaded demand served in the bundle $b \in B$ if awarded given that the demand scenario $\omega \in \Omega$ realizes.
$\sigma_{ij}^{b\ell}(\omega)$	Binary variable. $\sigma_{ij}^{b\ell} = 1$ if bundle b is part of the subset of bundles $\ell \in \mathcal{B}_{ij}$ covering the lane $(i, j) \in D$ such that current demand $f_{ij}(\omega)$ is satisfied for scenario $\omega \in \Omega$, $\sigma_{ij}^{b\ell} = 0$ otherwise.
$\varsigma_{ij}^{b\ell}(\omega)$	Binary variable. $\varsigma_{ij}^{b\ell} = 1$ if bundle b is part of the subset of bundles $\ell \in \mathcal{B}_{ij}$ covering the lane $(i, j) \in \hat{D}$ such that new auctioned demand $q_{ij}(\omega)$ is considered for scenario $\omega \in \Omega$, $\varsigma_{ij}^{b\ell} = 0$ otherwise.
$\tilde{\Pi}_b$	Total cost associated to empty repositioning movements in bundle $b \in B$.
$\mathbb{E}_\omega[\Pi_b(\omega)]$	Expected profit associated to auctioned lanes and synergetic current lanes related to bundle $b \in B$ for the realization of scenario $\omega \in \Omega$.
Γ_b	Set of synergetic arcs used to give continuity to auctioned lanes β_b in

Notation	Definition
	bundle $b \in B$. $\Gamma_b \subset \widehat{D} \cup \tilde{A}$.
x_{ij}^b	Flow on each repositioning arc $(i, j) \in \Gamma_b \cap \tilde{A}$ synergetic to the set of auctioned lanes $\beta_b \subset D$ in bundle $b \in B$.
$y_{ij}^b(\omega)$	Loaded flow of auctioned demand and synergetic current lanes $(i, j) \in \beta_b \cup (\Gamma_b \cap \widehat{D})$ associated to bundle $b \in B$ for the scenario $\omega \in \Omega$.
\mathcal{B}_{ij}	Set off mappings \mathcal{B} relating each demand arc $(i, j) \in D \cup \widehat{D}$ with every possible combination of bundles covering it.
N_b	Set of nodes considered in bundle $b \in B$. $N_b \subset N$.

A specific TL carrier participating of this auction also needs to consider the lanes of demand currently served \widehat{D} . Similarly, each lane $(i, j) \in \widehat{D}$ is associated to demand levels $f_{ij}(\omega)$ associated to each scenario $\omega \in \Omega$ with realization probability p_{ij}^ω known by the carrier. Likewise, each lane is associated to a shipment price \hat{p}_{ij} . Notice that this is private information known by the carrier. The carrier operates over a transportation network $G(N, A)$, where N is a set of nodes indicating the location of pickups/deliveries, and $A = \bar{A} \cup \tilde{A}$ indicates the set of arcs connecting these nodes. $\bar{A} = D \cup \widehat{D} \subset A$ is the subset of specific pickup/delivery arcs, and $\tilde{A} \subset A$ is the subset of repositioning arcs that connect every possible delivery to every possible pickup. Each pickup/delivery arc is associated to a loaded traversing cost \bar{c}_{ij} and pickup/delivery costs κ_i, κ_j such that the total arc cost $c_{ij} = \bar{c}_{ij} + \kappa_i + \kappa_j$, $\forall (i, j) \in \bar{A}$ for each TL. On the other hand, empty repositioning have a cost \tilde{c}_{ij} , $\forall (i, j) \in \tilde{A}$ per truck. Specifically, the carrier is not willing to serve any bundle below an expected profit threshold $\bar{\Pi}$.

The problem to solve is stated as follows. Given the conditions presented above, a carrier is asked to analyze the set of existing D and new \widehat{D} lanes to determine the best

combination of bundles B to submit to the TL CA that increases its expected profits. The stochastic MIQP (5.1)-(5.15) presents the mathematical formulation for this problem. There are five sets of variables in the this program: (i) $y_b(\omega)$ maximum amount of loaded demand that the carrier is willing to serve in the bundle $b \in B$ if awarded given that the demand scenario $\omega \in \Omega$ realizes, (ii) x_b truck volume associated to empty repositioning in the bundle $b \in B$ if awarded, (iii) p_b price per TL in the bundle b if awarded, (iv) binary variable $\sigma_{ij}^{b\mathcal{B}}(\omega) = 1$ if bundle b is part of the subset of bundles $\mathcal{B} \in \mathcal{B}_{ij}$ covering the lane $(i,j) \in D$ such that current demand $f_{ij}(\omega)$ is satisfied for scenario $\omega \in \Omega$, $\sigma_{ij}^{b\mathcal{B}}(\omega) = 0$ otherwise, and (v) binary variable $\zeta_{ij}^{b\mathcal{B}}(\omega) = 1$ if bundle b is part of the subset of bundles $\mathcal{B} \in \mathcal{B}_{ij}$ covering the lane $(i,j) \in \widehat{D}$ such that new auctioned demand $q_{ij}(\omega)$ for scenario $\omega \in \Omega$ is considered, $\zeta_{ij}^{b\mathcal{B}}(\omega) = 0$ otherwise. The objective function (5.1), subject to Constraints (5.2)-(5.15), maximizes the total expected profit of bundles associated to the expected profits for demand realizations $\mathbb{E}_\omega[\Pi_b(\omega)]$ (Constraint (5.2)) minus the costs $\widetilde{\Pi}_b$ associated to empty repositioning movements (Constraint (5.3)).

$$\max \mathbb{E}_\omega \left[\sum_{b \in B} \Pi_b(\omega) \right] - \sum_{b \in B} \widetilde{\Pi}_b \quad (5.1)$$

Constraint (5.2) computes the total expected profit for all bundles $b \in B$, associated to each loaded demand $y_b(\omega)$ realized in scenario $\omega \in \Omega$, i.e., the summation of expected profits for auctioned lanes $p_b - c_{ij}, (i,j) \in \beta_b$ and expected profits for current lanes $p_{ij} - c_{ij}, (i,j) \in \Gamma_b \cap \widehat{D}$.

$$\mathbb{E}_\omega \left[\sum_{b \in B} \Pi_b(\omega) \right] = \mathbb{E}_\omega \left[\sum_{b \in B} y_b(\omega) \left(\sum_{(i,j) \in \beta_b} (p_b - c_{ij}) + \sum_{(i,j) \in \Gamma_b \cap \widehat{D}} (\hat{p}_{ij} - c_{ij}) \right) \right] \quad (5.2)$$

Constraint (5.3) computes the total cost associated to empty repositioning for all bundles $b \in B$, i.e., the summation of empty costs \tilde{c}_{ij} for each arc $(i, j) \in \Gamma_b \cap \tilde{A}$ incurred by the bundled empty volume x_b , where $\Gamma_b \subset \tilde{A} \cup \hat{D}$ is the set of arcs (repositioning arcs and current lanes) synergetic to the auctioned lanes in bundle $b \in B$.

$$\sum_{b \in B} \tilde{\Pi}_b = \sum_{b \in B} x_b \sum_{(i,j) \in \Gamma_b \cap \tilde{A}} \tilde{c}_{ij} \quad (5.3)$$

Constraint (5.4) specifies that the expected profit for every individual bundle should be above a profit threshold $\bar{\Pi}$.

$$\bar{\Pi} \leq \tilde{\Pi}_b + \mathbb{E}_\omega[\Pi_b(\omega)] \quad \forall b \in B \quad (5.4)$$

Constraint (5.5) sets bundle price to the lowest reservation price for lanes in it. There are three important considerations behind this: (i) it is consistent with the concept of pricing for TL CAs, (ii) although the lowest reservation price is the highest for at least one lane, it is less than or equal to reservation prices in other lanes and, hence, more attractive, and (iii) although cost-based pricing would be lower, it would be prejudicial for carrier profits leaving money on the table that the shipper would be willing to pay.

$$p_b \leq p_{ij}, \forall (i, j) \in \beta_b \quad \forall b \in B \quad (5.5)$$

Constraint (5.6) and (5.7) indicate that the maximum empty x_b and expected loaded $y_b(\omega)$ volume in the bundle have to be assigned to each repositioning synergetic lane arc, i.e., $x_b = x_{ij}^b, \forall (i, j) \in \Gamma_b \cap \tilde{A}$, current synergetic lane, i.e., $y_b(\omega) = y_{ij}^b(\omega), \forall (i, j) \in (\Gamma_b \cup \hat{D})$, and auctioned lanes $y_b(\omega) = y_{ij}^b(\omega), \forall (i, j) \in \beta_b$ respectively in the bundle b .

$$x_b = x_{ij}^b \quad (5.6)$$

$$\begin{aligned}
& \forall (i, j) \in \Gamma_b \cap \tilde{A}, \forall b \in B \\
& y_b(\omega) = y_{ij}^b(\omega), \forall (i, j) \in \beta_b \cup (\Gamma_b \cup \widehat{D}) \\
& \forall b \in B, \forall \omega \in \Omega
\end{aligned} \tag{5.7}$$

Constraint (5.8) indicates that for every current lane $(i, j) \in \widehat{D}$, there exists at least a cover of bundles $\mathcal{b} \in \mathcal{B}_{ij}$ that satisfies its demand $f_{ij}(\omega)$ for the demand realization $\omega \in \Omega$.

$$\begin{aligned}
& \sum_{b \in B} y_{ij}^b(\omega) \sigma_{ij}^{b\mathcal{b}}(\omega) = f_{ij}(\omega), \forall \mathcal{b} \in \mathcal{B}_{ij} \\
& \forall (i, j) \in \widehat{D}, \forall \omega \in \Omega
\end{aligned} \tag{5.8}$$

Consequently, constraint (5.9) indicates that for every new auctioned lane $(i, j) \in D$ there might be bundles where demand $q_{ij}(\omega)$ is partially (or totally) covered for the demand realization $\omega \in \Omega$. In this profit maximization approach, constraint (5.9) prefers more profitable new lanes and even leaves unserved those that are not attractive for the trucking firm.

$$\begin{aligned}
& \sum_{b \in B} y_{ij}^b(\omega) \varsigma_{ij}^{b\mathcal{b}}(\omega) \leq q_{ij}(\omega) \\
& \forall \mathcal{b} \in \mathcal{B}_{ij} \subset B, \forall (i, j) \in D, \forall \omega \in \Omega
\end{aligned} \tag{5.9}$$

Constraint (5.10) gives flow conservation to every node $j \in N_b$, where N_b is the set of nodes covered by bundle $b \in B$. In essence, this constraints indicates that loaded realizations on a lane for scenario $\omega \in \Omega$ (first term left hand of equation) should be equal to the empty movements generated from that lane (second term right hand of equation), and vice versa.

$$\begin{aligned}
& \sum_{(i,j) \in \beta_b \cup (\Gamma_b \cap \widehat{D})} y_{ij}^b(\omega) + \sum_{(i,j) \in \Gamma_b \cap \tilde{A}} x_{ij}^b = \sum_{(j,k) \in \beta_b \cup (\Gamma_b \cap \widehat{D})} y_{jk}^b(\omega) + \sum_{(j,k) \in \Gamma_b \cap \tilde{A}} x_{jk}^b \\
& \forall j \in N_b \subset N, \forall b \in B
\end{aligned} \tag{5.10}$$

Finally, constraints (5.11)-(5.15) properly define non-negative, integer, and binary variables.

$$\begin{aligned} x_b &\in \mathbb{Z}^+ \\ \forall b &\in B \end{aligned} \tag{5.11}$$

$$\begin{aligned} y_b(\omega) &\in \mathbb{Z}^+ \\ \forall b &\in B, \forall \omega \in \Omega \end{aligned} \tag{5.12}$$

$$\begin{aligned} p_b &\geq 0 \\ \forall b &\in B \end{aligned} \tag{5.13}$$

$$\begin{aligned} \sigma_{ij}^{b\ell} &= \{1,0\} \\ \forall b &\in B, \forall \ell \in \mathcal{B}_{ij} \subset B, \forall (i,j) \in \widehat{D} \end{aligned} \tag{5.14}$$

$$\begin{aligned} \varsigma_{ij}^{b\ell} &= \{1,0\} \\ \forall b &\in B, \forall \ell \in \mathcal{B}_{ij} \subset B, \forall (i,j) \in D \end{aligned} \tag{5.15}$$

Song and Regan (2003 and 2005) and Lee et al. (2007) recognize the computational complexity of bidding advisory models for TL CAs. The complete enumeration of bundles grows exponentially with respect of the analyzed lanes. Furthermore, analyzing each bundle involves the solution of an NP-problem. This computational problem is aggravated by the quadratic expressions required to address pricing and demand segmentation in this research. Furthermore, program (5.1)-(5.15) suffers of critical constraint violations for different realizations of demand. Therefore, a solution procedure that accounts for these limitations and provides good quality bundles is required. BM \circ TS is a suite of algorithms proposed to account for these challenges. This model presents a balance between good quality bundles and a computationally tractable approach. The method is presented in the following section.

5.3 BM◦TS methodology

This section presents BM◦TS (Bidding Model for TL CA with Stochastic demand), a methodology to solve the problem presented in Section 5.2, which is illustrated in Figure 5.1. Table 5.2 presents specific notation used in the presentation of this method.

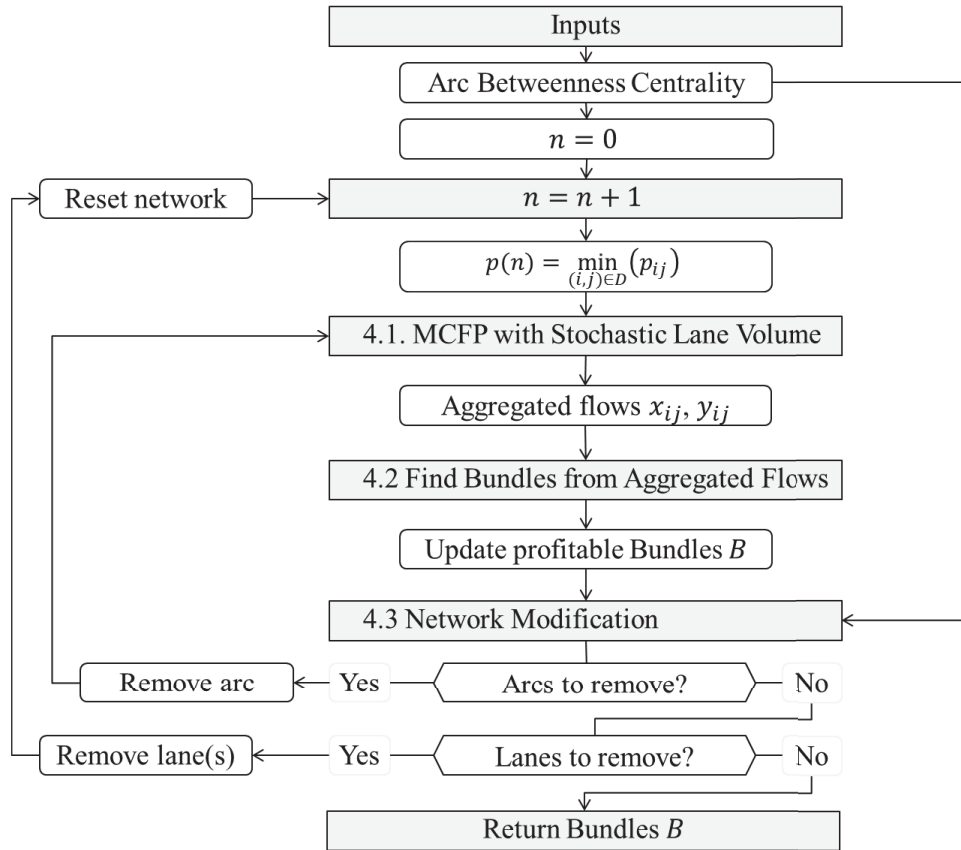


Figure 5.1 BM◦TS: bidding model for TL stochastic demand.

BM◦TS is initialized using the inputs described in the previous Section. Although each auctioned lane $(i, j) \in D$ is related to a reservation price p_{ij} , each bundle $b \in B$ have to be designed such that all bundled lanes in the set $\beta_b \subset D$ share the same price p_b . Notice that p_{ij} is the highest price the shipper is willing to pay for a lane, so it is willing to pay any price $p_b \leq p_{ij} \forall (i, j) \in \beta_b$. Following this idea, the BM◦TS is designed such

that all reservation prices are analyzed sequentially in an increasing order. The current global price analyzed at each iteration n is defined as $p(n)$. This price is used to update the expected profits associated to each auctioned lane and solve a minimum-cost flow (MCF) problem that accounts for stochastic demand (Subsection 5.3.1). This is a two-stage stochastic program where the first-stage variables x_{ij} determine the flow of empty trucks repositioned between current and auctioned lanes, and the second stage –stage variables $y_{ij}(\omega)$ indicate the expected demand realization associated to scenario $\omega \in \Omega$. Since these flows are aggregated, a post-processing method is required to find bundles based on the resulting tours, flows, and consistency of prices (Subsection 5.3.2). Then, the network is disrupted by removing an arc following the criteria presented in Subsection 5.3.3. Arc betweenness centrality (computed before starting the iterations) is an important network metric considered to define potential arcs to remove. This required in order to explore new combinations of lanes associated to the current $p(n)$. After considering all the possible removable arcs, the method removes the subset of auctioned lanes associated to the current price, i.e., $\{(i, j) \in D: p_{ij} = p(n)\} \subset D$ and a new iteration $n + 1$ starts with the next lowest price $p(n + 1)$. After analyzing prices for all auctioned lanes the method stops and the set of bundles B is returned.

Table 5.2 Specific mathematical notation for BM•TS

Notation	Definition
n	Iteration counter.
$p(n)$	Current global price associated to iteration n used to construct bundles and compute associated profits ensuring price consistency.
x_{ij}	First-stage variable accounting for empty repositioning.
$y_{ij}(\omega)$	Second-stage variables accounting for loaded movements associated to stochastic demand realizations.

Notation	Definition
M_{ij}	Upper bound for empty repositioning in arc $(i, j) \in \tilde{A}$.
π_b	Unitary profit per TL in bundle $b \in B$. $M_{ij} = \max_{\omega} \{q_{hi}(\omega), f_{hi}(\omega), q_{jk}(\omega), f_{jk}(\omega)\}$.
$y_{ij}(\Delta_{\omega})$	Second-stage variables accounting for the differential of demand between consecutive scenarios $y_{ij}(\omega)$ and $y_{ij}(\omega - 1)$ on lane $(i, j) \in D \cup \hat{D}$. $y_{ij}(\Delta_{\omega}) = y_{ij}(\omega) - y_{ij}(\omega - 1)$.
Δ_{ω}	Index identifying realizations of differentials of demand between consecutive scenarios $\omega \in \Omega$ and $(\omega - 1) \in \Omega$
$\mathcal{P}_{ij}^{\Delta_{\omega}}$	Probability of the realization of demand associated to the differential Δ_{ω} and lane $(i, j) \in D \cup \hat{D}$
$N(\Omega)$	Set of modified nodes to set the DE problem. $N(\Omega) = N_1(\Omega) \cup N_2(\Omega) \cup N_3(\Omega)$.
$N_1(\Omega)$	Subset of nodes representing each differential of demand.
$N_2(\Omega)$	Subset of dummy nodes for current lanes.
$N_3(\Omega)$	Subset of dummy nodes for deliveries.
$A(\Omega)$	Set of modified arcs to set the DE problem. $A(\Omega) = \bar{A}(\Omega) \cup \tilde{A}(\Omega)$.
$\bar{A}(\Omega)$	Subset of modified lanes. $\bar{A}(\Omega) = \hat{D}(\Omega) \cup D(\Omega)$
$\hat{D}(\Omega), D(\Omega)$	Subsets of lanes for current demand $\hat{D}(\Omega) = \hat{D}_1(\Omega) \cup \hat{D}_2(\Omega) \cup \hat{D}_3(\Omega)$ and auctioned demand $D(\Omega) = D_1(\Omega) \cup D_2(\Omega)$
$\hat{D}_1(\Omega), D_1(\Omega)$	Subsets of lanes between subsequent differential demand realizations
$\hat{D}_2(\Omega), D_2(\Omega)$	Subsets of lanes between subsequent differential demand realizations and corresponding delivery nodes
$\hat{D}_3(\Omega)$	Subset of current lanes from the first differential of demand realization to the dummy delivery node
y_{ij}	DE recourse variables
π_{ij}	Expected profit for arcs in the modified network associated to the DE problem
z_{ij}	Distribution of flows from stochastically optimized flows x_{ij} and y_{ij}
N_k	k^{th} subset of strongly connected nodes
t_b^k	Set of arcs forming a tour associated to bundle $b \in B$ obtained from the SC set N_k .
A'	Subset of modified arcs for tour construction. $A' = \{(i, j) \in A: z_{ij} > 0\} \subset A$
$\underline{\pi}_{ij}$	Expected marginal profit for auctioned lanes $(i, j) \in \beta_b$
Π_b	Expected total profit for bundle $b \in B$
BC_{ij}	Arc betweenness centrality for arc $(i, j) \in A$.

Notation	Definition
φ_{rs}^{ij}	Binary indicator. $\varphi_{rs}^{ij} = 1$ if arc $(i, j) \in A$ is traversed in the shortest path from $r \in N$ to $s \in N$, $\varphi_{rs}^{ij} = 0$ otherwise.
λ_{ij}	Binary indicator. $\lambda_{ij} = 1$ if arc $(i, j) \in A$ has been removed from the network, $\lambda_{ij} = 0$ otherwise.
\tilde{A}	Set of potential arcs considered for removal/perturbation. $\tilde{A} \subset \tilde{A}$.
r_{ij}	Capacity usage ratio. $r_{ij} = x_{ij}/u_{ij}$, $\forall (i, j) \in A$.
v_{ij}	Flow centrality criterion $y_{ij} = x_{ij} * BC_{ij}$, $\forall (i, j) \in A$.

After a general introduction to BM \circ TS, this section is organized as follows. Subsection 5.3.1 provides details about the formulation and solution of the proposed MCF problem with stochastic demand, Subsection 5.3.2 shows the proposed algorithm to construct bundles based on these TL flows, and Subsection 5.3.3 describes the proposed criteria used to modify the network such that it is possible to bundle different combinations of lanes.

5.3.1 Minimum-Cost Flow (MCF) Problem with Stochastic Lane Volume

This subsection proposes a special formulation of the Minimum-Cost Flow (MCF) problem that can be used to find bundles in the carrier network and accounts for uncertainty on TL lane volumes.

Several works have studied stochastic MCF and vehicle routing problems. Boyles and Waller (2010) propose a mean-variance model to the network flow problem with stochastic arc costs. They use two convex network optimization methods to solve the problem based on negative marginal cost cycles and network equilibrium. Additionally, they study the value of information. However, this model does not account for stochastic demand and capacity, which is more related to the current bundling problem.

Ding (2013) approaches the MCF with uncertain capacity using chance constraints. This Chapter transforms the uncertain MCF problem into a classical deterministic problem, and then solves it efficiently. Additionally, several authors have study the stochastic MCF in an optimization framework using fuzzy numbers (Ghatee and Mashemi, 2008, 2009a,2009b, Liu and Kao, 2004) study flow problems with uncertain arc lengths are using fuzzy numbers and transforming them to a crisp formulation. Although these works are useful to understand the distribution of optimal objective functions given the stochastic behavior of the system, they do not optimize to account such variations.

Optimization under uncertainty has been proposed for vehicle routing, i.e., fleet management, problems with uncertain demand and complex operational constraints, e.g., dynamic demand, multiple commodities, etc. (Sarimveis et al. 2008, Shi et al. 2014, Simão et al. 2009, Topaloglu and Powell, 2006). Following this idea, a two-stage stochastic MCF problem is postulate to find profitable tours that can be used to construct bundles accounting for demand uncertainty.

Consider the MCF where the decision variables $x_{ij}, (i, j) \in \tilde{A}$ (first-stage variables), determine the volume of TLs repositioned after traversing a loaded lane. The loaded demand $y_{ij}(\omega), (i, j) \in \bar{A}$ (second-stage variables) is unknown but its realization is determined by the occurrence of scenario $\omega \in \Omega$, where Ω is the finite set of demand scenarios considered in the analysis.

The objective function (5.16) in this problem is maximizing the profit obtained from the summation of the revenues after charging the expected demand realization at each lane minus the cost associated to empty and loaded movements. For convenience, the

objective function is written as a minimization problem, which implies inverting the signs for costs and prices without loss of generality. BM \circ TL solves this problem is solved for each price instance n , i.e., same price for all auctioned lanes ($p_{ij} = p(n), \forall (i, j) \in D$).

$$\min \sum_{(i,j) \in \bar{A}} c_{ij} x_{ij} + \mathbb{E}_{\omega} \left[\sum_{(i,j) \in \bar{A}} (c_{ij} - p_{ij}) y_{ij}(\omega) \right] \quad (5.16)$$

This objective function is subject to a set of random constraints. The summation of empty trucks x_{hi} repositioned from each delivery h to the next loaded movement from i should be equal to the expected realization of loaded trucks $y_{ij}(\omega)$ directed to the corresponding pick up node j (Constraint (5.17)).

$$\sum_{h:(h,i) \in \bar{A}} x_{hi} = y_{ij}(\omega), \forall (i, j) \in \bar{A} \quad (5.17)$$

$\forall \omega \in \Omega$

Likewise, the expected realization of TLs $y_{ij}(\omega)$ moved from i to j should be equal to the total empty trucks x_{jk} repositioned to the next pickup k after delivering at j (Constraint (5.18)).

$$y_{ij}(\omega) = \sum_{k:(j,k) \in \bar{A}} x_{jk} \quad (5.18)$$

$\forall (i, j) \in \bar{A}, \forall \omega \in \Omega$

The volume of loaded trucks $y_{ij}(\omega)$ on each lane $(i, j) \in \hat{D}$ currently served by the carrier has to be equal to the expected demand realization $f_{ij}(\omega)$ (Constraint (5.19)).

$$y_{ij}(\omega) = f_{ij}(\omega) \quad (5.19)$$

$\forall (i, j) \in \hat{D} \subset \bar{A}, \forall \omega \in \Omega$

On the other hand, the volume of loaded trucks $y_{ij}(\omega)$ on each auctioned lane $(i, j) \in D$ can be less than or equal to the demand realization $q_{ij}(\omega)$ (Constraint (5.20)).

$$\begin{aligned} y_{ij}(\omega) &\leq q_{ij}(\omega) \\ \forall (i,j) \in D \subset \tilde{A}, \forall \omega \in \Omega \end{aligned} \quad (5.20)$$

Repositioned x_{ij} and loaded trucks $y_{ij}(\omega)$ TL volumes are non-negative integer numbers (Constraint (5.21)). Empty repositioning x_{ij} is bounded by a consistent and sufficiently large number, e.g., $M_{ij} = \max_{\omega} \{q_{hi}(\omega), f_{hi}(\omega), q_{jk}(\omega), f_{jk}(\omega)\}$ (Constraint (5.22)).

$$\begin{aligned} x_{ij}, y_{ij}(\omega) &\in \mathbb{Z}^+ \\ \forall (i,j) \in A, \forall \omega \in \Omega \end{aligned} \quad (5.21)$$

$$\begin{aligned} 0 &\leq x_{ij} \leq M_{ij} \\ \forall (i,j) \in \tilde{A}, \forall \omega \in \Omega \end{aligned} \quad (5.22)$$

The solution space for the stochastic integer program (IP) (5.16)-(5.22) is infeasible for scenarios different to the actual realizations of demand. Hence, a deterministic equivalent (DE) problem is proposed to solve the stochastic IP. This is achieved using a series of network transformations for the current and auctioned lanes. Network transformations are usually proposed to solve stochastic routing problems, e.g., Topaloglu and Powell (2006). The DE IP uses soft constraints and appropriate penalties in the objective function to handle violations and compute the repositioning flows x_{ij} that account for stochastic demand.

Concepts related to the demand realization probabilities are introduced before presenting the proposed network transformation. Without loss of generality assume that the set $\Omega = \{1, \dots, \omega, \dots, |\Omega|\}$ is sorted such that $f_{ij}(1) < \dots < f_{ij}(\omega) < \dots < f_{ij}(|\Omega|), \forall (i,j) \in \tilde{D}$, and $q_{ij}(1) < \dots < q_{ij}(\omega) < \dots < q_{ij}(|\Omega|), \forall (i,j) \in D$, which implies that $y_{ij}(1) < \dots < y_{ij}(\omega) < \dots < y_{ij}(|\Omega|)$. Likewise, let $y_{ij}(0) = 0$ and

$y_{ij}(\Delta_\omega) = y_{ij}(\omega) - y_{ij}(\omega - 1)$ be the differential of demand between $y_{ij}(\omega)$ and $y_{ij}(\omega - 1)$. Thus, any realization of loaded movements can be represented as a function of its previous realizations (Equation (5.23)).

$$y_{ij}(\omega) = \sum_{s \in \{1, \dots, \omega\} \subset \Omega} y_{ij}(\Delta_s), \forall (i, j) \in \bar{A}, \forall \omega \in \Omega \quad (5.23)$$

Following this idea, Equation (5.24) describes the probability $\mathcal{P}_{ij}^{\Delta_\omega}$ for the realization of $y_{ij}(\Delta_\omega)$. Notice that $\mathcal{P}_{ij}^{\Delta_{|\Omega|}} < \mathcal{P}_{ij}^{\Delta_{|\Omega|-1}} < \dots < \mathcal{P}_{ij}^{\Delta_2} < \mathcal{P}_{ij}^{\Delta_1} = 1$.

$$\mathcal{P}_{ij}^{\Delta_\omega} = \sum_{s \in \Omega: \omega \leq s} \mathcal{P}_{ij}^s \quad (5.24)$$

Figure 5.2 illustrates the network transformations required to set the DE problem. This requires the definition of new sets of nodes $N(\Omega)$ and arcs $A(\Omega) = \bar{A}(\Omega) \cup \tilde{A}(\Omega)$, where the modified set arcs $A(\Omega)$ is composed by a modified set of lanes $\bar{A}(\Omega)$ and a modified set of empty repositioning arcs $\tilde{A}(\Omega)$. Subsequently, $\bar{A}(\Omega) = \hat{D}(\Omega) \cup D(\Omega)$ aggregates the modified sets of current $\hat{D}(\Omega)$ and auctioned $D(\Omega)$ lanes.

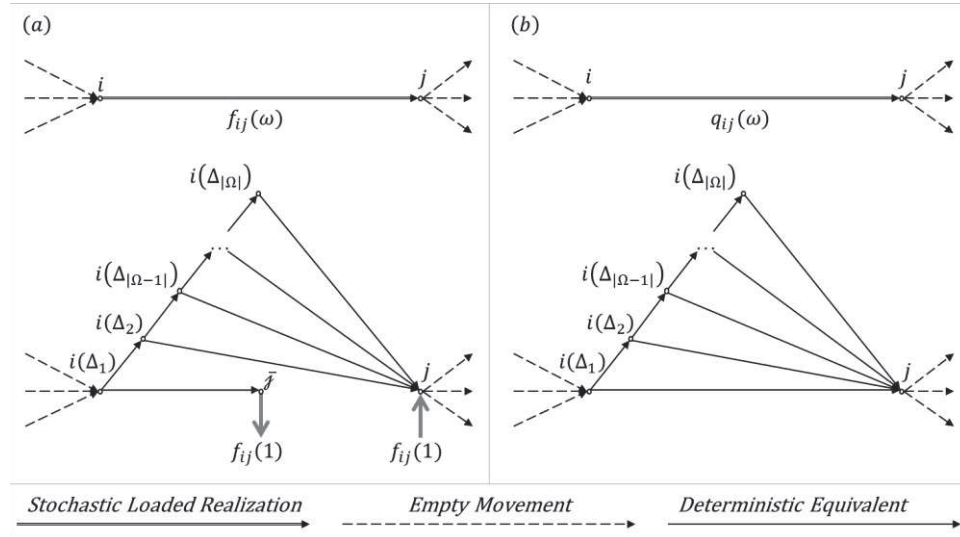


Figure 5.2 Network transformation for (a) current lanes, and (b) auctioned lanes

The new set of nodes $N(\Omega) = N_1(\Omega) \cup N_2(\Omega) \cup N_3(\Omega)$ is composed by three subsets defined as follows. For each lane $(i, j) \in \widehat{D} \cup D = \bar{A}$ node $i \in N$ is replaced a set of $|\Omega|$ nodes representing each differential Δ_ω , i.e., $N_1(\Omega) = \{i(\Delta_\omega), \forall \omega \in \Omega, \forall i \in N: (i, j) \in \bar{A}\}$. Furthermore, a second set of dummy nodes $N_2(\Omega) = \{\bar{j}, \forall (i, j) \in \widehat{D}\}$ is generated, where a node $\bar{j} \in N_2(\Omega)$ is created for each current lane $(i, j) \in \widehat{D}$. The third subset corresponds to delivery nodes $N_3(\Omega) = \{j \in N: (i, j) \in \bar{A}\}$.

Each current lane $(i, j) \in \widehat{D}$ is replaced by a group of lanes according to the modified set of arcs $\widehat{D}(\Omega) = \widehat{D}_1(\Omega) \cup \widehat{D}_2(\Omega) \cup \widehat{D}_3(\Omega)$ (Figure 5.2(a)). The first subset $\widehat{D}_1(\Omega) = \{(i(\Delta_{\omega-1}), i(\Delta_\omega)): \forall i(\Delta_\omega), i(\Delta_{\omega-1}) \in N_1(\Omega), \omega \in \Omega \setminus \{1\}\}$ is composed by arcs between subsequent differential realizations, i.e., $i(\Delta_{\omega-1})$ and $i(\Delta_\omega)$. The second subset $\widehat{D}_2(\Omega) = \{(i(\Delta_\omega), j): \forall i(\Delta_\omega) \in N_1(\Omega), \forall j \in N_3(\Omega), \omega \in \Omega \setminus \{1\}, (i, j) \in \widehat{D}\}$ connects each differential realization $i(\Delta_\omega)$ with the corresponding delivery node j . The third subset $\widehat{D}_3(\Omega) = \{(i(\Delta_1), \bar{j}): \forall i(\Delta_1) \in N_1(\Omega), \forall \bar{j} \in N_2(\Omega), (i, j) \in \widehat{D}\}$ is defined for arcs from the first differential realization $i(\Delta_1)$ to the corresponding dummy delivery node \bar{j} .

Similarly, each auctioned lane $(i, j) \in D$ is replaced by a group of lanes as described by the set of modified auctioned lanes $D(\Omega) = D_1(\Omega) \cup D_2(\Omega)$ (Figure 5.2(b)). The first subset $D_1(\Omega) = \{(i(\Delta_{\omega-1}), i(\Delta_\omega)): \forall i(\Delta_\omega), i(\Delta_{\omega-1}) \in N_1(\Omega), \omega \in \Omega \setminus \{1\}\}$ accounts for arcs between subsequent differential realizations $i(\Delta_{\omega-1})$ and $i(\Delta_\omega)$, and $D_2(\Omega) = \{(i(\Delta_\omega), j): \forall i(\Delta_\omega) \in N_1(\Omega), \forall j \in N_3(\Omega), (i, j) \in D\}$ connects each differential realizations $i(\omega)$ with the corresponding delivery node j .

Finally, each repositioning arc $(i, j) \in \tilde{A}$ is properly redefined forming the set of modified repositioned arcs $\tilde{A}(\Omega) = \{(i, j(\Delta_1)): \forall j(\Delta_1) \in N_1, (i, j) \in \tilde{A}\}$.

In the DE problem, the variables $y_{i(\Delta_\omega)j}$ describe the recourse actions to take if the scenario associated to the differential of demand Δ_ω occurs. The objective function in this problem maximizes the total expected profit for the distribution of trucks in the network. If the expected demand takes place it is priced, which compensates the regular cost of the movement and generates a profit. Otherwise, trucks travel empty and the movement is associated to a net cost (negative profit). Empty repositioning cost on each arc $(i, j(\Delta_1)) \in \tilde{A}(\Omega)$ is equal to the cost for its equivalent $(i, j) \in \tilde{A}$, i.e., $c_{ij(\Delta_1)} = c_{ij}$. Each auctioned lane $(i(\Delta_\omega), j) \in D_2(\Omega)$ is associated to the cost of its analogous arc $(i, j) \in D$ but its price corresponds to the one for the current iteration n , i.e., $c_{i(\omega)j} = c_{ij}$ and $p_{i(\omega)j} = p(n)$. For current lanes $(i(\omega), j) \in \widehat{D}_2(\Omega) \cup \widehat{D}_3(\Omega)$, price and cost are associated to the ones in the original arc $(i, j) \in \widehat{D}$, i.e., $c_{i(\omega)j} = c_{ij}$ and $p_{i(\omega)j} = p_{ij}$. Thus, the expected profit for a loaded lane $(i, j) \in \tilde{A}$ in scenario $\omega \in \Omega$ is determined by Equation (5.25) (minimization and opposite signs are used for convenience), where the first summation accounts for the cost of empty repositioning and the second for the expected profit associated to each differential of demand.

$$\min \sum_{(i, j(\Delta_1)) \in \tilde{A}(\Omega)} c_{ij(\Delta_1)} x_{ij(\Delta_1)} + \sum_{(i(\Delta_\omega), j) \in D_2(\Omega) \cup \widehat{D}_2(\Omega) \cup \widehat{D}_3(\Omega)} (c_{i(\Delta_\omega)j} - \mathcal{P}_{ij}^{\Delta_\omega} p_{i(\Delta_\omega)j}) y_{i(\Delta_\omega)j} \quad (5.25)$$

Notice that in the objective function (5.25), the probability $\mathcal{P}_{ij}^{\Delta_\omega}$ only multiplies the lane price because if Δ_ω realizes then TL trips will be associated to a loaded ℓ expected profit $\pi_{ij}^\ell(\Delta_\omega) = (c_{ij} - p_{ij})\mathcal{P}_{ij}^{\Delta_\omega}$. On the other hand, if this lane is part of a bundle but

demand does not realize the empty expected profit will be $\pi_{ij}^e(\Delta_\omega) = c_{ij}[1 - \mathcal{P}_{ij}^{\Delta_\omega}]$.

Hence, the total expected profit is $\pi_{ij} = \pi_{ij}^\ell + \pi_{ij}^e = c_{ij} - \mathcal{P}_{ij}^{\Delta_\omega} p_{ij}$.

The artificial flows $y_{i(\Delta_{\omega-1})i(\Delta_\omega)}$ do not contribute to the objective function but are required to give continuity to each Δ_ω realization in a recursive fashion as described by constraint (5.26), which is common for current and auctioned lanes. For this constraint, let $\bar{A}_1(\Omega) = D_1(\Omega) \cup \hat{D}_1(\Omega)$ and $\bar{A}_2(\Omega) = D_2(\Omega) \cup \hat{D}_2(\Omega)$.

$$\begin{aligned} y_{i(\Delta_{\omega-1})i(\Delta_\omega)} &= y_{i(\Delta_\omega)j} + y_{i(\Delta_\omega)i(\Delta_{\omega+1})} \\ \forall \omega \in \Omega \setminus \{1\}, \forall (i(\Delta_{\omega-1}), i(\Delta_\omega)) &\in \bar{A}_1(\Omega), \forall (i(\Delta_\omega), j) \in \bar{A}_2(\Omega): (i, j) \in \bar{A} \end{aligned} \quad (5.26)$$

Constraints (5.27)-(5.31) are exclusive for the set of current lanes \hat{D} . Constraint (5.27) indicates that the summation of empty trucks repositioned from each previous delivery at h (left hand side) is equivalent to the flow heading to the dummy arc $y_{i(\Delta_1)\bar{f}}$ plus the auxiliary flow $y_{i(\Delta_\omega)i(\Delta_{\omega+1})}$. Notice that the first term in the right hand side is fixed to $f_{ij}(1)$ (Constraint (5.28)) and the second term is defined by the first instance of the recursive constraint (5.26), i.e., $y_{i(\Delta_1)i(\Delta_2)}$. Recall that $\mathcal{P}_{ij}^{\Delta_1} = 1$ and hence, it is known that at least $f_{ij}(1)$ loaded movements will occur on lane (i, j) . Additionally, since this is a current lane served by the carrier, it has to be guaranteed that at least this demand is satisfied, which is assured by the equality of constraint (5.27) and (5.28). Notice that $y_{i(\Delta_1)i(\Delta_2)}$ acts as a slack variable that let the problem to attract more flow than the smallest realization and, hence, preparing for other uncertain realizations.

$$\begin{aligned} \sum_{h: (h, i(\Delta_1)) \in \bar{A}(\omega)} x_{hi(\Delta_1)} &= y_{i(\Delta_1)\bar{f}} + y_{i(\Delta_1)i(\Delta_2)} \\ \forall i(\Delta_1) \in N_1(\Omega), \forall (i(\Delta_1), \bar{f}) &\in \hat{D}_3(\Omega), \forall (i(\Delta_1), i(\Delta_2)) \in \hat{D}_1(\Omega): (i, j) \in \hat{D} \end{aligned} \quad (5.27)$$

$$\begin{aligned} y_{i(\Delta_1)\bar{j}} &= f_{ij}(1) \\ \forall (i(\Delta_1), \bar{j}) \in \widehat{D}_3(\Omega): (i, j) \in \widehat{D} \end{aligned} \quad (5.28)$$

Once the certain demand $f_{ij}(1)$ is served, the possibility of serving the differential of demand $f_{ij}(\Delta_\omega) = f_{ij}(\omega) - f_{ij}(\omega - 1)$ exists at each node $i(\Delta_\omega)$ if this improves the corresponding expected profits. Constraint (5.29) accounts for this possibility bounding the loaded flow on each arc $(i(\Delta_\omega), j)$.

$$\begin{aligned} y_{i(\Delta_\omega)j} &\leq f_{ij}(\omega) - f_{ij}(\omega - 1) \\ \forall \omega \in \Omega \setminus \{1\}, \forall (i(\Delta_\omega), j) \in \widehat{D}_2(\Omega) \end{aligned} \quad (5.29)$$

Given that differentials of demand $f_{ij}(\Delta_\omega)$ are potentially served from nodes $i(\Delta_\omega)$ associated to the lower levels of Ω , the maximum amount of flow (capacity) that can go upwards on each auxiliary lane $(i(\Delta_{\omega-1}), i(\Delta_\omega)) \in \widehat{D}_1(\Omega)$ reduces gradually as Δ_ω approaches to $\Delta_{|\Omega|}$. Constraint (5.30) formally defines this condition. Recall that this is possible because the sequential ω is set such that it maps to the increasingly sorted $f_{ij}(\omega)$.

$$\begin{aligned} y_{i(\Delta_{\omega-1})i(\Delta_\omega)} &\leq f_{ij}(|\Omega|) - f_{ij}(\omega - 1) \\ \forall \omega \in \Omega \setminus \{1\}, \forall (i(\Delta_{\omega-1}), i(\Delta_\omega)) \in \widehat{D}_1(\Omega) \end{aligned} \quad (5.30)$$

Constraint (5.31) specifies that the sum of the certain demand $f_{ij}(1)$ (first term left hand side) plus the assigned trucks that account for uncertain loaded movements (second term left hand side) is equivalent to the total empty trucks generated from the expected deliveries on current lanes (right hand side).

$$\begin{aligned} f_{ij}(1) + \sum_{s \in \Omega: (i(\Delta_s), j) \in \widehat{D}_2(\Omega)} y_{i(\Delta_s)j} &= \sum_{k(\Delta_1) \in N_1(\Omega): (j, k(\Delta_1)) \in \widehat{A}(\Omega)} x_{jk(\Delta_1)} \\ \forall j \in N_3(\Omega): (i, j) \in \widehat{D} \end{aligned} \quad (5.31)$$

Constraints (5.32)-(5.35) are exclusive for the set of auctioned lanes D . Constraint (5.32) indicates that the summation of empty trucks repositioned from each previous

delivery at h (left hand side) is equivalent to the flow $y_{i(\Delta_1)j}$ heading to the arc associated to the certain demand on the auctioned lane $(i, j) \in D$ plus the auxiliary flow $y_{i(\Delta_\omega)i(\Delta_{\omega+1})}$. Different to constraint (5.27) (analogous to current lanes), the first term in the right hand side is not fixed to $q_{ij}(1)$. Without loss of generality, let $q_{ij}(0) = 0$. Then, Constraint (5.33) gives the possibility to include an auctioned lane in the bundle by either serving a fraction of certain demand, i.e., $0 < y_{i(\Delta_1)j} \leq q_{ij}(1) = q_{ij}(1) - q_{ij}(0)$, or not or not, i.e., $y_{i(\Delta_1)j} = 0$. Similarly, $y_{i(\Delta_1)i(\Delta_2)}$ gives the possibility to account for more demand with lower realization probability if this improves the corresponding expected profits. For $\omega > 1$ the Constraint (5.33)'s intuition is similar to Constraint (5.29).

$$\sum_{h:(h,i(\Delta_1)) \in \tilde{A}} x_{hi(\Delta_1)} = y_{i(\Delta_1)j} + y_{i(\Delta_1)i(\Delta_2)} \quad (5.32)$$

$$\forall i(\Delta_1) \in N_1(\Omega), \forall (i(\Delta_1), j) \in D_2(\Omega), \forall (i(\Delta_1), i(\Delta_2)) \in D_1(\Omega): (i, j) \in D$$

$$\begin{aligned} y_{i(\Delta_\omega)j} &\leq q_{ij}(\omega) - q_{ij}(\omega - 1) \\ \forall \omega \in \Omega, \forall (i(\Delta_\omega), j) &\in D_2(\Omega) \end{aligned} \quad (5.33)$$

Constraint (5.34) is analogous to constraint (5.30). The same intuitive explanation can be easily adapted to the case of actioned lanes D .

$$\begin{aligned} y_{i(\Delta_{\omega-1})i(\Delta_\omega)} &\leq q_{ij}(|\Omega|) - q_{ij}(\omega - 1) \\ \forall \omega \in \Omega \setminus \{1\}, \forall (i(\Delta_{\omega-1}), i(\Delta_\omega)) &\in D_1(\Omega) \end{aligned} \quad (5.34)$$

Constraint (5.35) specifies that the sum of assigned trucks that account for uncertain loaded movements (left hand side) is equivalent to the total empty trucks generated from the expected deliveries on current lanes (right hand side).

$$\sum_{s \in \Omega: (i(\Delta_s), j) \in D_2(\Omega)} y_{i(\Delta_s)j} = \sum_{k(\Delta_1) \in N_1(\Omega): (j, k(\Delta_1)) \in \tilde{A}(\Omega)} x_{jk(\Delta_1)} \quad (5.35)$$

$$\forall j \in N_3(\Omega): (i, j) \in D$$

Consistently, the volume of repositioned and loaded trucks are set to non-negative integer numbers in Constraint (5.36), and empty repositioning is bounded by a sufficiently large number, e.g., M_{ij} in Constraint (5.37). M_{ij} is defined as in Constraint (5.22).

$$x, y \in \mathbb{Z}^+ \quad (5.36)$$

$$\begin{aligned} 0 \leq x_{ij(1)} \leq M_{ij} \\ \forall (i, j(1)) \in \tilde{A}(\Omega) \end{aligned} \quad (5.37)$$

In general, stochastic programs suffer from the curse of dimensionality and this one is not the exception. However, the specific structure of the DE IP (5.25)-(5.37) makes possible to frame it as a deterministic MCF problem (Ahuja et al. 1995). Interestingly, there are several algorithms that solve the MCF problem in polynomial time. Király and Kovács (2012) summarize many of them (Table 4.3 in Chapter 4), which is beneficial for its solution.

5.3.2 Find bundles from aggregated flows

After solving the special MCF presented above (DE IP (5.25)-(5.37)), the resulting flows were optimized to account for uncertainty. Expression (5.38) computes the resulting distribution of flows z_{ij} on each arc $(i, j) \in A = \bar{A} \cup \hat{A} = (\hat{D} \cup D) \cup \hat{A}$ of the original network.

$$z_{ij} = \begin{cases} x_{ij(\Delta_1)} & \forall (i, j) \in \tilde{A}: (i, j(\Delta_1)) \in \hat{A}(\Omega) \\ y_{i(\Delta_1)\bar{j}} + \sum_{s \in \Omega \setminus \{1\}} y_{i(\Delta_s)j} & \forall (i, j) \in \hat{D}: (i(\Delta_1)\bar{j}) \in \hat{D}_3(\Omega), (i(\Delta_s), j) \in \hat{D}_2(\Omega) \\ \sum_{s \in \Omega} x_{i(\Delta_s)j} & \forall (i, j) \in D: (i(\Delta_s), j) \in D_2(\Omega) \end{cases} \quad (5.38)$$

However, z_{ij} aggregates several tours and it is not clear what lanes are suitable to be bundled together. Then, a disaggregating method is required. The objective of this method is finding tours of TL flow that are subsequently used to generate bundles.

Tarjan (1972) proposes an efficient algorithm $O(|A||N|)$ to find independent subsets $N_k \subset N: N_k \cap N_{k+1} = \emptyset$ of strongly connected (SC) components in a directed graph. The special characteristic of a SC set N_k is that for each pair of nodes $i, j \in N_k$ there exist paths $i \Rightarrow j$ and $j \Rightarrow i$, i.e., a round tour b starting from any node i passing by any other node j traversing the set of arcs t_b^k . The recursive depth-first search used by Tarjan's algorithm to find every N_k can also be used to obtain the corresponding tours $\{t_b^k\}$. Having each t_b^k is important to collect flow x_b associated to the current global price $p(n)$ for auctioned lanes. This information will determine whether t_b^k is considered to generate a bundle $b \in B$ or not.

The proposed algorithm explores strongly connected tours t_b^k and relates each of them to its smallest flow x_b . This flow is iteratively removed, which changes the characteristics of the network and allows the detection of new strongly connected tours. When a tour is found, arcs are differentiated between auctioned lanes β_b , and supplementary arcs Γ_b , i.e., current lanes and empty repositioning arcs. A bundle is constructed only if there is an auctioned lane $(i, j) \in \beta_b$ with a price equivalent to the current global price, i.e., $p_{ij} = p(n)$, and the expected profit is greater than or equal to the accepted one, i.e., $\Pi_b \geq \bar{\Pi}$. Profits are computed considering the estimations from the DE IP (5.25)-(5.37) (Equation (5.39)). The output of this method is an updated set of bundles B , where each bundle $b \in B$ covers the auctioned lanes $\beta_b \subset D$ at a price p_b , up

to a desired flow level x_b on each lane. The method to find bundles from aggregated flows is summarized as follows:

Step 2.1: Define the sub-network $G(N, A')$ where $A' = \{(i, j) \in A: z_{ij} > 0\}$

Step 2.2: Use Tarjan's algorithm over $G(N, A')$ to find SC components N_k and underlying tours t_b^k

Step 2.3: For each k, b pair:

Step 2.3.1: Compute tour flow $x_b = \min\{z_{ij}: (i, j) \in t_b^k\}$

Step 2.3.2: Segregate arcs into auctioned lanes $\beta_b = t_b^k \cap D$ and current lanes $\Gamma_b = t_b^k \setminus \beta_b$

Step 2.3.3: if there exists an auctioned lane whose price is equal to the current global, i.e., $\exists(i, j) \in \beta_b: p_{ij} = p(n)$, set $p_b = p(n)$ and continue to Step 2.3.4, else omit b and go to Step 2.3.7.

Step 2.3.4: Compute the expected marginal profit for each auctioned lane $(i, j) \in \beta_b$ (Equation (5.39))

$$\underline{\pi}_{ij} = z_{ij}^{-1} \sum_{s \in \Omega} (c_{i(\Delta_s)j} - p_b) y_{i(\Delta_s)j}, \forall (i, j) \in D \quad (5.39)$$

Step 2.3.4: Compute tour profits (Equation (5.40))

$$\Pi_b = x_b \left(\sum_{(i,j) \in \Gamma_b} \pi_{ij} + \sum_{(i,j) \in \beta_b} \underline{\pi}_{ij} \right) \quad (5.40)$$

Step 2.3.5: If the expected profit is acceptable, i.e., $\Pi_b \geq \bar{\Pi}$, then continue to Step 2.3.6, else omit bundle b and go to Step 2.3.7.

Step 2.3.6: Add tour b to the set of bundles $B = B \cup \{b\}$, where b is associated to the bundle $\{\beta_b, x_b, p_b\}$.

Step 2.3.7 Reduce flows in the current sub-network, i.e., $z_{ij} = z_{ij} - x_b, \forall (i, j) \in t_b^k$

Step 2.4: If there are unanalyzed flows in the network, i.e., $\sum_{(i,j) \in A} z_{ij} > 0$ go to Step 2.1, else stop.

5.3.3 Network modification

The special MCF problem solution outputs an optimal set of flows that maximizes expected profits accounting for demand uncertainty. Such flows are used to update the set of optimal bundles B . However, there is high risk if only one stochastically optimal set of bundles is submitted to the auction. This is because if competitors have better prices for lanes in any of these bundles, the carrier will likely lose those lanes, and, hence, losing all lanes within the corresponding bundles. Therefore, a method to explore other good bundles is required.

Here, the question is how to find another a set of flows that can produce different bundles at the same expected profit or within a narrow gap from it. The proposed answer is achieving it using appropriate network modifications, i.e., perturbations.

The challenge is finding the proper perturbation criteria that consider the unused capacity on the arcs and a metric of arc attractiveness. Perturbing arcs that are very attractive for low-cost tours is not desirable because they are usually overlapped by several bundles. So, a criterion where perturbation goes from less to more desirable arcs is envisioned.

Another important question is how to account for network effects? This is important because an isolated arc can be unattractive but very relevant when jointly analyzed with

other lanes. In this sense, a metric considering the importance or centrality of the arcs is required.

Betweenness Centrality (Anthonisse 1971, Freeman 1977, Newman 2010) is used to identify important central nodes/arcs in a network by counting the number of times these elements are used as bridges in the shortest paths between every node duplet. So, arc betweenness centrality is used as part of the selection criteria to perturb the network. Worst case running time for its computation is $O(|N|^3)$. It is performed once at the beginning of BM-TS when the original network $G(N, A)$ has not been perturbed. Arc betweenness centrality BC_{ij} is formally defined in Equation (5.41), where the binary variable $\varphi_{rs}^{ij} = 1$ if arc $(i, j) \in A$ is traversed in the shortest path from $r \in N$ to $s \in N$, $\varphi_{rs}^{ij} = 0$ otherwise.

$$BC_{ij} = \sum_{(r,s) \in A} \varphi_{rs}^{ij} \quad (5.41)$$

After updating bundles, the perturbation procedure presented below is applied to remove an arc from the network. Let $\lambda_{ij} = 1$ indicate that the arc (i, j) has been removed from the network, otherwise $\lambda_{ij} = 0$ ($\lambda_{ij} = 0, \forall (i, j) \in A$ at the beginning of each iteration n). Let $\tilde{\Lambda} = \{(i, j) \in \tilde{A} \setminus \{\tilde{A}_1 \cup \tilde{A}_2\} : z_{ij} > 0, \lambda_{ij} = 0\}$ indicate the set of potential arcs considered for removal/perturbation. The subset $\tilde{\Lambda} \subset \tilde{A}$ indicates that only empty repositioning arcs with flow in the current solution, i.e., $z_{ij} > 0$, not removed before, i.e., $\lambda_{ij} = 0$, are considered to be removed. However, two types of arcs are not removed: (1) backhauls arcs, i.e., $\tilde{A}_1 = \{(j, i) \in \tilde{A} : (i, j) \in \tilde{A}\}$, and (2) those giving continuity to

current lanes, i.e., $\tilde{A}_2 = \{(i, j) \in \tilde{A} : (\cdot, i), (j, \cdot) \in \tilde{D}\}$. The algorithm for network modification is described as follows.

Step 3.1: Obtain z_{ij} from Equation (5.38)

Step 3.2: For all $(i, j) \in \tilde{\Lambda}$

Step 3.2.1: Compute capacity usage ratio $r_{ij} = z_{ij}/M_{ij} \in (0, 1]$

Step 3.2.2: Compute flow centrality criterion $v_{ij} = z_{ij} * BC_{ij}$

Step 3.2.3: Define the subset $\tilde{\Lambda}' \subset \tilde{\Lambda}$ of potential arcs associated to the maximum capacity usage ratio r_{ij} , i.e., $\tilde{\Lambda}' = \{(i, j) \in \tilde{\Lambda} : r_{ij} = \max\{r_{ij}\}\}$

Step 3.2.4: Select one arc (i, j) from $\tilde{\Lambda}'$ with the minimum selection criterion v_{ij} , i.e., $(i, j) = \operatorname{argmin}_{(i, j) \in \tilde{\Lambda}'} (v_{ij})$

Step 3.2.5: Remove $(i, j) \in \tilde{\Lambda}$ from the network, i.e., $A = A \setminus \{(i, j)\}$, and set $\lambda_{ij} = 1$.

The perturbation procedure prioritizes arc removal based on (1) zero or small unused capacity captured by r_{ij} , and (2) low flow and low centrality (periphery) captured by v_{ij} . Concept (1) gives flexibility to use such capacity in later iterations. Concept (2) protects important arcs that can overlap in several bundles. The selected arc is removed from the network and not considered in next iterations because $\lambda_{ij} = 1$.

The n^{th} iteration of BM \circ TS stops when it is not possible to select an arc to remove, i.e., $\nexists (i, j) \in \tilde{\Lambda}$. Notice that arcs related to current demand are maintained in the network. This guarantees that new auctioned lanes in the resulting bundles either have synergies with the current lanes or do not affect their current operation.

The possibility of removing arcs resulting in bundles with unacceptable profits exists. When this happens, the last removed arc (i, j) is added back to $G(N, A)$, i.e., $A = A \cup \{(i, j)\}$, removal criteria are estimated again and a new arc is selected. Notice that $\lambda_{ij} = 1$ remains and this arc is not part of the removal choice set.

5.4 Numerical results

This section presents a numerical example illustrating the use of BM \circ TS, which is coded in C++. Király and Kovács (2012) test the computational efficiency of different MCF software packages and algorithms. They find the C++ Library for Efficient Modeling and Optimization in Networks (LEMON) (Dezső et al. 2011) and its Network Simplex to be one of the most competent algorithms to solve the MCF problem in large scale networks. Therefore, these modules are integrated to BM \circ TS. LEMON is developed by the Computational Infrastructure for Operations Research (COIN-OR) and also used for network manipulation. Other modules are developed by the authors. Experiments are run in a desktop with the following characteristics: Processor Intel® Core™2 Duo CPU E8400 @ 3.00GHz, Installed memory (RAM) 4.00GB.

Table 5.3 Numerical example data

Arc Type	Origin	Destination	Price	Cost	1 - Low		2 - Medium		3 - High	
					Vol.	Prob.	Vol.	Prob.	Vol.	Prob.
Current	0	1	13	3	141	85%	213	10%	269	5%
Empty	1	0		3						
Empty	1	4		4						
Empty	1	2		1						
Auctioned	2	3	17	3	199	34%	223	53%	230	13%
Empty	3	0		1						
Empty	3	4		2						
Empty	3	2		3						

Arc Type	Origin	Destination	Price	Cost	1 - Low		2 - Medium		3 - High	
					Vol.	Prob.	Vol.	Prob.	Vol.	Prob.
Auctioned	4	5	9	2	108	32%	114	20%	196	48%
Empty	5	0		5						
Empty	5	4		2						
Empty	5	2		1						

Consider a carrier participating of a TL CA. It currently serves the lane $\{(0,1)\} = \hat{D}$ and will build bids for the set of auctioned lanes $D = \{(2,3), (4,5)\}$. For each lane, three scenarios of demand realizations are known, i.e., low $\omega = 1$, medium $\omega = 2$, and high $\omega = 3$ ($\Omega = \{1,2,3\}$). The prices (\$), costs (\$), volumes (TL/month) and probabilities (%) for each demand realization are presented in Table 5.3. Likewise, empty repositioning cost (\$) is available for the corresponding arcs.

Table 5.4 present the numerical results after running BM \circ TS, where eight bundles are built and computation time is less than 1 second. The first three pre-bundles (1.1, 1.2, and 1.3) are associated to the bundle $b = 1$ for the auctioned lane $\{(2,3)\} = \beta_1$, notice that this lane is more profitable when served conjointly with the current lane $\{(0,1)\} \in \Gamma_1$ up to a volume of $x_{1,1} = 141$ TL/month. However, it is still profitable for demand levels up to $x_{1,3} = 223$ TL/month (served alone). Therefore the maximum desired volume is $x_1 = 223$ TL/month. The price charged for this bundle is $p_1 = \$17$, which is consistent to the corresponding reservation price of the lane. The next three pre-bundles (2.1, 2.2, and 2.3) are associated to bundle $b = 2$ for the set of auctioned lanes $\{(2,3), (4,5)\} = \beta_2$. The maximum desired volume for this bundle is $x_2 = 141$. The price charged for each lane in this bundle is $p_2 = \$9$, which is consistent to the rules of TL CAs and was not properly captured by previous models in literature. Notice that lane (2,3) (whose reservation price

is $p_{23} = \$17$) can be priced at \$9 when combined with lanes in this bundle, one of the benefits of economies of scope. The last two pre-bundles (3.1,3.2) are associated to the bundle $b = 3$ for the auctioned lane $\{(4,5)\} = \beta_1$, which the carrier is willing to serve by itself up to a volume $x_3 = 196$ TL/month. The price charged for this bundle is $p_3 = \$9$ (reservation price).

Table 5.4 Preliminary numerical results

Pre Bundle	Max TL Vol.	Price	Expected Profit	Auctioned Lanes	Synergetic Lanes	Profit per TL/month
1.1	141	17	2972.28	$\{(2,3)\}$	$\{(0,1)\}$	21.08
1.2	82	17	826.56	$\{(2,3)\}$		10.08
1.3	223	17	2131.88	$\{(2,3)\}$		9.56
2.1	141	9	1906.32	$\{(2,3),(4,5)\}$	$\{(0,1)\}$	13.52
2.2	82	9	626.48	$\{(2,3),(4,5)\}$		7.64
2.3	55	9	358.60	$\{(2,3),(4,5)\}$		6.52
3.1	114	9	338.58	$\{(4,5)\}$		2.97
3.2	196	9	243.04	$\{(4,5)\}$		1.24

A post-processing analysis indicates that a set B with three bundles can be submitted to the auction. The triplets $\{\beta_b, x_b, p_b\}$ associated to each bundle $b \in B$ are summarized in Table 5.5. Interesting insights are obtained from these bundles. Bid $b = 1$ bids for lane (2,3) up to its middle level realization $\omega = 2$, i.e., $y_{23} = y_{2(\Delta_1)3} + y_{2(\Delta_2)3} = 223$, which is anticipated as the expected profit for its highest differential of demand Δ_3 is actually a net cost, i.e., $\pi_{23}(\Delta_3) = c_{23} - \mathcal{P}_{23}^{\Delta_3} p_{23} = \0.79 . This is not the case for $b = 3$, where the entire differential levels for (4,5) are associated to expected net profits and, hence, it is worth bidding for the highest level of demand that compensates other empty repositioning costs. Finally, the distribution associated to the current lane (0,1) indicates

that the probabilities of the differential realizations Δ_2 (medium) and Δ_3 (high) are not high enough to have expected profits beneficial for the carrier. Indeed, these probabilities are associated to net expected costs. This features are reflected in bundle $b = 2$ where (2,3) and (4,5) have significant synergies with (0,1) at its lower level.

Table 5.5 Set of bundles B submitted to the auction

Bundle b	Lanes β_b	Max volume per lane x_b	Price p_b
1	{(2,3)}	223	17
2	{(2,3),(4,5)}	141	9
3	{(4,5)}	196	9

The next section summarizes the current work and provides future research directions.

5.5 Conclusions

This Chapter studies TL CAs and presents BM \circ TS, a bidding model that can be used by TL carriers to construct bundles and account for stochastic demand. BM \circ TS determines the sets of lanes that represent expected profits to the carrier which are accompanied with the corresponding bidding prices and maximum TL volumes that the carrier is willing to serve for each lane in the bundle.

Thus, the main contributions of BM \circ TS to the literature related to bidding advisory models in TL CAs are threefold: (1) using a value-based pricing approach to build bundles that maximize the expected profits of the bundles and properly handle prices following the rules of CAs, (2) using demand segmentation to determine the maximum TL volume that the carrier is willing to serve within each bundle, and (3) incorporating demand uncertainty in the construction of bundles.

In addition to these contributions, BM \circ TS finds bundles at a tractable computational time. This is important and meaningful for trucking analysts that require evaluating networks with hundreds of lanes in a TL CA setting. Computational burden is reduced by a novel two-stage MCF problem with stochastic lane volume that can be solved efficiently using available MCF algorithms. This is possible through network transformations that convert the two-stage stochastic problem into its deterministic equivalent and find aggregated flows optimized for uncertainty. Furthermore, the Chapter presents a novel approach to find tours and build bundles from these aggregated flows.

A numerical example illustrates the application of BM \circ TS and shows its ability to account for stochastic demand under different demand realization scenarios. Likewise, it takes advantage of economies of scope that generate synergies between lanes and propitiate their aggrupation.

CHAPTER 6. BENEFITS OF IN-VEHICLE CONSOLIDATION IN LESS THAN TRUCKLOAD FREIGHT TRANSPORTATION OPERATIONS

6.1 Introduction

Researchers and public agencies have proposed consolidation policies as an alternative to increase truck payload utilization and mitigate externalities produced by freight transportation. Understanding and enhancing the economic mechanisms that lead to freight consolidation can ease the implementation of these strategies, increase profits for shippers and carriers, and reduce freight-related negative externalities. An important mechanism that has recently been studied for cost reduction in the freight industry is combinatorial auctions, where carriers construct bids considering direct shipments (Truckload operations). Several bidding advisory models have been proposed for this purpose. However, there are economies of scale that can be achieved if shipments are consolidated inside vehicles, which have not been explored in the construction of competitive bids. This chapter investigates such benefits and provides insights on the competitiveness and challenges associated to the development of consolidated bids (suitable for Less-than-Truckload operations). Consolidated bids are constructed using a multi-commodity one-to-one pickup-and-delivery vehicle routing problem that is solved using a branch-and-price algorithm.

The numerical experiment shows that non-consolidated bids are dominated by consolidated bids, which implies that this type of operation can increase the likelihood of a carrier to win auctioned lanes, while increasing its profits margins over truckload companies (non-consolidated bids), and keeping the reported benefits that combinatorial auctions represent for shippers

Defining appropriate routes is important for the carriers to distribute the variable cost among their clients, achieving different levels of economy, and quoting competitive shipping prices. To understand how this has been done previously, we briefly review the microeconomic operation of trucking firms. The total income perceived by a carrier is the sum of the prices charged to each shipment transported in a time period. Likewise, the total cost is the summation of costs associated with the delivering routes plus fixed costs. The total profit is defined by the difference between these two. For example, for a carrier serving the shipment h charged with a price p_h following the route r_h , the total profit associated with this shipment is $\Pi(h) = p_h - c(r_h) - c_o$, where $c(r_h)$ is the total cost related to the operation of route r_h , and c_o are fixed costs. To observe how route definition affects the value of the prices, assume that there is another shipper that needs transportation for a shipment k and requests a quote from the carrier. If the carrier decides to charge a price p_k for that shipment, the corresponding total profit would be $\Pi(h, k) = p_h + p_k - c(r_{h \cup k}) - c_o$, where $r_{h \cup k}$ is the route serving both shipments h and k . For a rational carrier it is expected that $\Pi(h) \leq \Pi(h, k)$, and therefore, $c(r_{h \cup k}) - c(r_h) \leq p_k \leq \hat{p}_k$, where \hat{p}_k is an upper bound determining the maximum price that the shipper is willing to pay for this service. Notice that if the carrier can serve both shipments following the same route, then $c(r_{h \cup k}) = c(r_h) + \Delta c$ where Δc is a small cost

increment and, therefore, $\Delta c \leq p_k \leq \hat{p}_k$. Furthermore, p_k might be reduced down to Δc without affecting the carrier profits. But, if the new shipper accepts to pay a price $p_k > \Delta c$ that would imply more profits for the carrier. This shows that bidding for lanes complementary to the routes currently operated by the carrier has the potential of reducing the prices charged to these lanes and increasing the probability of getting the contracts. The variable costs for these routes depend on operational characteristics of the carrier, e.g., the number of vehicles operated, total distance traveled, repositioning of vehicles, geographical location of the pickups and deliveries, current commitments, location of the depot, among others. Considering all these elements in the construction of a bid is not easy and potentially leads to suboptimal solutions.

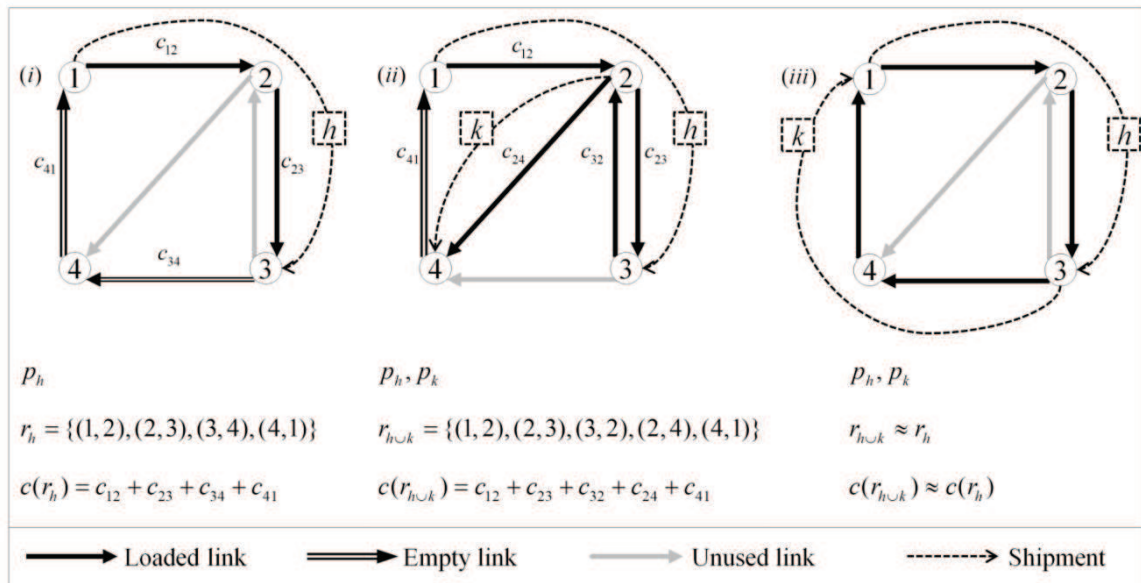


Figure 6.1 Economies of scope achieved by truckload (TL) firms.

Previous bidding advisory models (Song and Regan, 2003, and 2005, Wang and Xia, 2005, Lee, et al, 2007) focus primarily on carriers with TL operations, where shipments are sent directly from origin to destination using an exclusive truck –similar to the use of

taxi by passengers. This type of operation is mainly driven by economies of scope. These economies are achieved when there are follow-up loads that reduce the number of empty trips in a given trip chain/route (Caplice 1996; Jara-Diaz 1981; Jara-Diaz 1983). This concept is illustrated with the following case based on the previous example, as well as the directed network and demand scenarios shown in Figure 6.1 (i, ii, and iii). Without loss of generality, let us assume unitary traversing costs c_{ij} for each link (i, j) in the network. For a TL carrier in Scenario (i) (Figure 6.1), the route $r_h^{(i)}$ involves picking up the shipment h at node 1, traveling to node 2, delivering at node 3 and returning empty to node 1 via node 4, i.e., trip chain $r_h^{(i)} = \{(1,2), (2,3), (3,4), (4,1)\}$, and total cost $c(r_h^{(i)}) = 4$ units (notice that the superscript in parenthesis indicates the referred scenario). In scenario (ii), the TL carrier has to pickup k at node 2 and deliver it at node 4. This implies a new trip chain $r_{h \cup k}^{(ii)} = \{(1,2), (2,3), (3,2), (2,4), (4,1)\}$ with total cost $c(r_{h \cup k}^{(ii)}) = 5$ units. Thus, the price charged to the new shipment $p_k^{(ii)}$ has to be defined in the range $[\Delta c^{(ii)}, \hat{p}_k]$, where $\Delta c^{(ii)} = c(r_{h \cup k}^{(ii)}) - c(r_h^{(i)}) = 1$, i.e., $p_k^{(ii)} \in [1, \hat{p}_k]$. Finally, in scenario (iii) the TL carrier has to pickup shipment k at node 3 and deliver in node 1, which correspond to the same trip chain presented in scenario (i), i.e., $r_{h \cup k}^{(iii)} = r_h^{(i)}$. Thus, $c(r_{h \cup k}^{(iii)}) \approx c(r_h^{(i)}) = 4$ and economies of scope are achieved by guaranteeing loaded follow up trips that decrease the lower bound of $p_k^{(iii)}$ to $\Delta c^{(iii)} \approx 0$, i.e., $p_k^{(iii)} \in (0, \hat{p}_k]$. By contrasting scenarios (ii) and (iii) it can be concluded that under a fixed price $p_k = p_k^{(ii)} = p_k^{(iii)}$, the profits for scenario (iii) are greater than those for scenario (ii), and, therefore, a carrier would be able to submit more competitive prices in a combinatorial

auction for the bundle in scenario (iii). Notice that the equality $c(r_{h \cup k}^{(iii)}) = c(r_k^{(i)})$ does not strictly hold because there is a small additional cost related to uploading/downloading k and a marginal fuel consumption increment due to the change from empty to loaded trips, however these two values are assumed to be very similar.

The bidding advisory models developed in previous research are not clearly applicable by companies that follow Less-Than-Truckload (LTL) operations. In these operations, shipments are consolidated –similarly to the use of buses by passengers– in order to achieve economies of scale and density in addition to the economies of scope (Caplice 1996; Jara-Diaz 1981; Jara-Diaz 1983). According to Caplice (1996) there are three types of consolidation: at the origin, i.e. waiting for an appropriate size to be shipped; inside vehicles, i.e. sharing transportation with shipments from other origins; and/or in terminals, e.g. hub-and-spoke operations. The economies of consolidation are illustrated with a follow up of the previous example. Assume that shipments h and k are suitable for consolidation in the truck operated by an LTL carrier. Thus, the demand considered in scenario (ii) can be served by the same route for scenarios (i) and (iii), i.e., picking up the shipment h at node 1, picking up shipment k at node 2, traveling to node 3 with h and k in the same truck, delivering h at node 3, then delivering k at node 4, and finally returning empty to node 1, i.e.,

$$r_{h \cup k}^{LTL(ii)} = r_{h \cup k}^{(iii)} = r_h^{(i)} = \{(1,2), (2,3), (3,4), (4,5)\}, \quad c(r_{h \cup k}^{LTL(ii)}) = c(r_{h \cup k}^{(iii)}) = c(r_k^{(i)}) =$$

4 units, and, therefore, $p_k^{LTL(ii)} \in (0, \hat{p}_k]$. Notice that from an economic perspective the

LTL strategy dominates the TL strategy because the LTL carrier can always bid for k at lower prices than the TL carrier. At equilibrium the LTL carrier would obtain the demand

k at a price $p_k^{LTL(ii)} = 1 - \Delta p$, where Δp is a small quantity close to zero. Notice that in scenario (iii) it is not possible to consolidate k and h . Therefore, both TL and LTL strategies have the same probability of being awarded to serve shipment k .

However, TL operations are more flexible than LTL because they can easily adapt to changing demand. This is because LTL operations require a set of consolidation facilities where shipments are sorted, transferred to larger vehicles, and sent to other facilities to repeat this process or to be prepared for final delivery. Nevertheless, in-vehicle consolidation can be seen as a hybrid approach that integrates the flexibility and economies of scope of TL operations with the economies of scale of LTL operations.

The objective of this Chapter is to quantify the benefits to carriers of in-vehicle consolidation in the bidding construction process in a freight transportation combinatorial auction. The focus is not on the design of the auction per se but in demonstrating that in-vehicle consolidation in LTL framework can offer substantial gains to carriers. A multi-commodity one-to-one pickup-and-delivery vehicle routing problem (m-PDVRP) is used to determine partitions of the network (bundles) that minimize operational costs. Minimizing costs is important because a bundle with a fixed price can be served by different combinations of trucks/routes but only the one with minimum cost maximizes the profits of the carrier. Similarly, if several carriers bid for the same bundle but have different operational costs, the one with lower costs can always price lower obtaining profits that are greater than or equal to those perceived by the others. Consequently, low costs propitiate low prices which increases the probability of winning lanes that are part of a bundle and do not deteriorate profits when competing against other carriers that have higher costs. The m-PDVRP formulation explicitly incorporates the following carrier

characteristics: a single depot where all routes start and end, a fleet of vehicles with specific capacity, and a consolidation policy where a single vehicle can carry shipments from different origin-destination OD pairs. In addition to the economies of scope considered in previous research, this formulation takes advantages of economies of density and scale to identify low cost routes. The m-PDVRP is a mixed-integer program (MIP) where binary variables determine the assignment of vehicles to road segments in the transportation network and continuous decision variables determine the amount of freight inside a vehicle at each segment of the network. Since using commercial software to solve this NP-hard problem is not practical - real world applications involve 1800 lanes on average (Caplice & Sheffi 2006) - a solution algorithm based on the branch-and-price methodology (Barnhart et al. 1998; Desaulniers et al. 1998) is proposed. The theoretical framework is problem specific, which means that no standard software exists to implement it. To the best of our knowledge, this is the first attempt to incorporate LTL features in the assessment of bids in combinatorial auctions for freight transportation. Then, a numerical experiment is conducted to contrast consolidated bids against non-consolidated bids. The results show that, from the pure economic perspective, consolidated (LTL) bids are more profitable and have higher probability of being selected than non-consolidated (TL) bids.

This Chapter is organized as follows: Section 6.1 presents the problem motivation and a review of previous work. Section 6.2 presents the problem definition, mathematical notation, and the MIP formulation. Section 6.3 presents the branch-and-price solution algorithm. Section 6.4 presents examples and computational experiments from the

proposed methodology. Finally, Section 6.5 presents conclusions and future research directions.

6.2 Problem notation, definition, and formulation

This section presents the mathematical formulation to identify the most valuable set of lanes (bundle) that can be submitted by a carrier in the freight market assuming that in-vehicle consolidation (LTL carrier) is allowed. Each auctioned lane presents the amount of demand that goes from a specific origin to a specific destination. Likewise, the set of lanes can be partitioned into subsets, where each of them is served by a truck and represents a bundle that can be submitted to the combinatorial auction. Thus, the maximum number of partitions corresponds to the maximum number of trucks available by the carrier. This idea for bundle definition is akin to the bidding advisory model proposed by Lee, et al (2007), where a vehicle routing problem is used to determine optimal routes serving direct shipments (TL operation) and each route determines the lanes covered by a bundle. Furthermore, the problem approached in this Chapter corresponds to a multi-commodity one-to-one pickup-and-delivery vehicle routing problem (m-PDVHR), which has not been widely studied in previous literature. Although the formulation below is similar to the one presented by Hernández-Pérez, and Salazar-González (2009) for the multi-commodity one-to-one traveling salesman problem (m-PDTSP), it considers multiple vehicles (a distinctive difference between the TSP and the VRP). To the best of our knowledge the only previous work related to m-PDVHR correspond to the one by Psaraftis (2011), who uses dynamic programming to solve the problem but presents results that are limited to networks with low number of nodes (up to 4) and vehicles (up to 2). On the other hand, several works have been presented for LTL

network design and vehicle routing (Andersem et al. 2011, Baykasoglu & Kaplanoglu 2011, Crainic et al. 2009, Smilowitz et al. 2003). However, these works are based on the consolidation and coordination of shipments through facilities (hubs and spokes) that are strategically located in the transportation network, which is a rigid assumption that is associated to high investments in infrastructure, and do not consider the flexibility of in-vehicle consolidation for combinatorial auctions discussed in the introduction section. The mathematical notation followed throughout the Chapter is presented in Table 6.1. Subsequent subsections present a clear definition of the problem, modeling assumptions, and problem formulation.

Table 6.1 Mathematical notation

Notation	Definition
$G(N, A)$	Transportation network (complete directed graph)
N	Set of all nodes in the transportation network. $N = N' \cup \{0\}$. Where 0 identifies the depot.
N'	Subset of nodes where loads have to be picked up or delivered. $N' \subset N$
A	Set of all directed arcs in the transportation network. $A = \{(i, j) : i \in N, j \in N\}$
a_{ijt}	Binary coefficient equal to one if arc $(i, j) \in A$ is covered by the deployment $t \in T$ or zero otherwise
c_{ij}	Traversing cost of arc $(i, j) \in A$
c_t	Cost associated with the deployment of trucks $t \in T$
p^{rs}	Amount of freight to be moved in the auctioned lane $(r, s) = \{(r, s) \in A : r \in N', s \in N'\}$
V	Fleet of vehicles initially located at the depot (node $\{0\}$)
Q	Capacity or maximum utilization of the vehicles.
t	A deployment of trucks covering all nodes in the network. $t \in T$
T	Set of all deployments of trucks.

M	Any subset of nodes not containing the depot $M \subset N'$.
x_{ij}^v	Binary variable equal to one if arc $(i, j) \in A$ is traversed by vehicle $v \in V$, zero otherwise.
$l_{ij}^{rs,v}$	Amount of freight picked up in $r \in N'$ to be delivered in $s \in N'$ traversing arc $(i, j) \in A$ inside vehicle $v \in V$.
λ_t	Convexity variable associated with the deployment of trucks $t \in T$

6.2.1 Problem definition

In this problem, given a geographic area divided into regions connected by transportation infrastructures, a shipper placing a combinatorial auction to assign a set of lanes over carriers that serve this area, and a carrier participating in the auction with a depot located in the area, a fleet of vehicles with specific capacities, and a LTL policy of in-vehicle consolidation, it is required to determine the most valuable bid (route or routes), to be submitted by the carrier to such auction. The most valuable bid is defined as the one that covers all demand and minimizes the total system cost.

To define the problem mathematically, let $G = (N, A)$ be a complete directed graph composed by a set of nodes $N = N' \cup \{0\}$ and a set of arcs A . The subset $N' \subset N$ corresponds to nodes where loads have to be picked up or delivered. The depot is numbered as node 0. Each arc $(i, j) = \{(i, j) \in A : i \in N, j \in N\}$ is associated with a traversing cost c_{ij} satisfying the triangle inequality ($c_{ij} < c_{ik} + c_{kj}, \forall i, j, k \in N$). Each auctioned lane $(r, s) = \{(r, s) \in A \mid r \in N', s \in N'\}$ is associated with an amount of freight p^{rs} . There is a fleet of vehicles V at the depot, with specific capacity Q . The problem determines the routes that minimize the total system traversing cost, such that all

vehicles start and finalize their routes at the depot 0, each p^{rs} is served, and v 's payload never exceeds Q .

6.2.2 Problem assumptions

The formulation presented below is based on the following assumptions:

- Only the most valuable bundle per vehicle is generated, i.e., route that minimizes the total system traversing cost
- Time windows are not considered
- All vehicles have the same capacity
- Bundle valuation is based on the cost rather than the profits or other criteria.
- All demand must be served
- There is no constraint on the maximum tour length
- Vehicles leave the depot empty and return empty.
- All vehicles are used
- Fleet size cannot exceed the number of freight lanes.

The above assumptions can be relaxed leading to more complex formulations. Constraints such as maximum tour length and differential vehicle capacity can be easily incorporated within the framework presented in this work. However, for the sake of simplicity, this Chapter focuses on the basic version of the problem. Once this has been fully understood, the framework can be extended to accommodate other constraints.

6.2.3 Problem formulation

The m-PDTSP is formulated as a MIP model with two sets of variables: binary variables x_{ij}^v that take value 1 if arc $(i, j) \in A$ is traversed by vehicle $v \in V$ and

continuous nonnegative variables $l_{ij}^{rs,v}$ indicating the amount of freight picked up in $r \in N'$ to be delivered in $s \in N'$ traversing arc $(i, j) \in A$ inside vehicle $v \in V$. Sub-tour elimination constraints are considered in (6.5), where M is any subset of nodes not containing the depot $M \subset N'$.

$$\min \sum_{v \in V} \sum_{(i,j) \in A} x_{ij}^v * c_{ij} \quad (6.1)$$

$$\text{s.t.} \quad \sum_{v \in V} \sum_{j \in N} x_{ij}^v = 1; \quad \forall i \in N' \quad (6.2)$$

$$\sum_{j \in N} x_{0j}^v = 1; \quad \forall v \in V \quad (6.3)$$

$$\sum_{j \in N} x_{ji}^v = \sum_{j \in N} x_{ij}^v; \quad \forall i \in N, \forall v \in V \quad (6.4)$$

$$\sum_{i \in M} \sum_{j \in M} x_{ij}^v \leq |M| - 1; \quad \forall M \subset N', \forall v \in V \quad (6.5)$$

$$\sum_{v \in V} \sum_{j \in N'} l_{ij}^{is,v} = p^{is}; \quad \forall s \in N, \forall i \in N' \quad (6.6)$$

$$\sum_{v \in V} \sum_{j \in N'} l_{ji}^{ri,v} = p^{ri}; \quad \forall r \in N, \forall i \in N' \quad (6.7)$$

$$\sum_{j \in N'} l_{ji}^{rs,v} = \sum_{j \in N'} l_{ij}^{rs,v}; \quad \forall i \in N', \forall r \in N \setminus \{i\}, \forall s \in N \setminus \{i\}, \forall v \in V \quad (6.8)$$

$$l_{i0}^{rs,v} = 0 \text{ and } l_{0j}^{rs,v} = 0; \quad \forall i \in N', \forall r \in N, \forall s \in N, \forall v \in V \quad (6.9)$$

$$\sum_{r \in N} \sum_{s \in N} l_{ij}^{rs,v} \leq Q * x_{ij}^v; \quad \forall i \in N', \forall j \in N', \forall v \in V \quad (6.10)$$

$$x_{ij}^v \in \{1, 0\}; \quad \forall i \in N, \forall j \in N, \forall v \in V \quad (6.11)$$

$$l_{ij}^{rs,v} \geq 0; \quad \forall i \in N, \forall j \in N, \forall r \in N, \forall s \in N, \forall v \in V \quad (6.12)$$

In this formulation, the objective function (6.1) minimizes the total system traversing cost. Constraint (6.2) specifies that each node must be visited by one vehicle. Constraint (6.3) ensures that all vehicles are used. Constraint (6.4) defines the vehicle flow conservation at each node and constraint (6.5) relates to the sub-tour elimination, which increases the number of constraints exponentially with respect to the number of nodes. The demand satisfaction constraints are given by (6.6) for pickups and (6.7) for deliveries. Constraint (6.8) determines the payload flow conservation. Constraint (6.9) specifies that vehicles leave the depot empty and return empty. Constraint (6.10) indicates that loads can be transported only on traversed links and its total amount cannot exceed the vehicle capacity. Constraint (6.11) is for binary variables and (6.12) for non-negative continuous variables.

The following section presents a solution algorithm that follows the branch-and-price methodology. This algorithm is proposed since it is difficult to solve the above formulation using standard MIP solvers.

6.3 Solution methodology

This section presents a branch-and-price (B&P) solution algorithm (Barnhart et al. 1998, Desaulniers et al. 1998) developed to solve the MIP presented before. This methodology improves the computational time and can handle larger instances of the problem than those handled by commercial solvers. B&P is the integration of Dantzig-Wolfe decomposition and column generation into a branch-and-bound (B&B) algorithm. The three modules that integrate the B&P algorithm, i.e., B&B, Master problem (MP),

and Sub-problem (Sub-P), are presented in the corresponding subsections below. Finally, the integration of these modules in the B&P framework is presented at the end of the section.

6.3.1 Branch-and-bound (B&B)

In general, B&B is a built-in procedure used to solve integer programs (IPs) and MIPs by commercial software. This algorithm constructs a tree of feasible solutions while searching for an optimal integer solution.

In the B&B algorithm, a search tree is built based on the solution of sequential linear programs (LPs), a relaxation of the original IP problem, where each node represents one of these solutions. To accelerate the process, nodes can be terminated, or fathomed, if the node solution is: greater than the incumbent solution (in the case of a minimization problem), infeasible, or lesser than the incumbent solution and integer. In the latter case the node solution updates the incumbent solution. If none of these cases hold, i.e., the solution of the LP at the node is lesser than the incumbent solution but not integer, a non-integer variable (or set of variables) is selected and branched, i.e., two new branches are added to the current node where each branch corresponds to an integer constraint of the branched variable (or set of variables). For example, if after solving the LP relaxation of a problem it turns out that the optimal solution is lesser than the incumbent solution and there exists a variable $x = \alpha$ such that α is a non-integer number, two new instances (branches) of the LP are generated, i.e. one where the constraint $x = \lfloor \alpha \rfloor$ is added to the LP and another where $x = \lceil \alpha \rceil$ is added. $\lfloor \alpha \rfloor$ and $\lceil \alpha \rceil$ are the nearest lower and higher integers to α respectively. There are different searching strategies to find an optimal solution (e.g., depth-first-, or breath-first-search).

The special characteristic that differentiates B&B from B&P is that a column generation procedure based on Dantzin-Wolfe decomposition (Desrosiers and Lübbecke, 2005) is implemented at each node of the tree rather than solving the LP relaxation of the original problem. In order to apply these concepts, the original MIP has to be decomposed into a Master Problem and a Sub-Problem.

6.3.2 Master problem (MP)

This section presents the Master Problem (MP) used in the B&P algorithm. The MP is the LP solved at each node of the B&B tree embedded in the B&P algorithm.

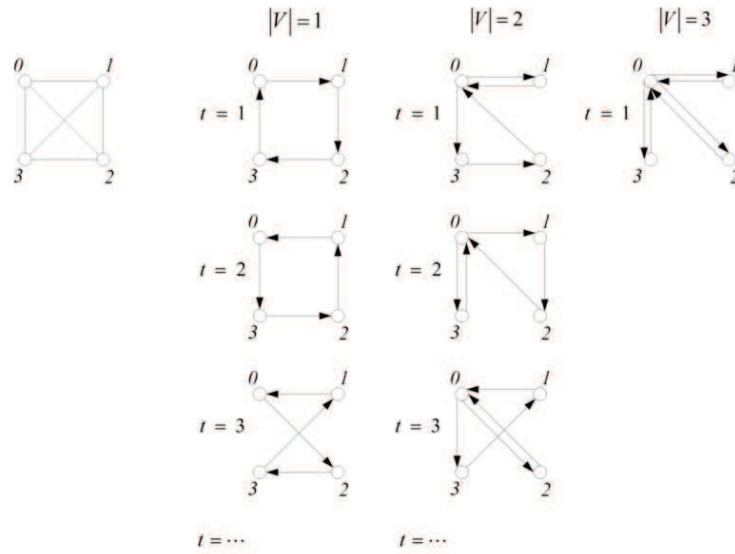


Figure 6.2. Examples of deployments of trucks t for one ($|V| = 1$), two ($|V| = 2$), and three ($|V| = 3$) trucks in a network with four nodes.

Since the original problem is a MIP, it is expressed as a LP using Dantzig-Wolfe decomposition which allows the representation of integer variables, as convex combinations of extreme points of this space. Applying these concepts in the MIP (6.1)-

(6.12) implies the identification of a common solution space that defines the corresponding convexity variables. It is observed that constraints (6.2)-(6.5), and (6.11) split the set of nodes without the depot N' in $|V|$ subsets. The arcs in each of these subsets are those covered by a Hamiltonian cycle connected to the depot. Examples of these covers are presented in Figure 6.2. Each combination of cycles is called a deployment of trucks and identified with the sub index $t \in T$, where T is the set of all truck deployments in a network $G(N, A)$. Therefore, the variables representing whether a link is selected or not x_{ij} are expressed as convex combination of these deployments through convexity variables λ_t , i.e., $x_{ij} = \sum_t a_{ijt} \lambda_t : \sum_t \lambda_t = 1, \lambda_t \geq 0$, where a_{ijt} is a binary coefficient equal to one if arc $(i, j) \in A$ is covered by the deployment $t \in T$ or zero otherwise. The resulting MP is presented below.

$$\min \sum_{t \in T} c_t \lambda_t \quad (6.13)$$

$$\text{s.t.} \quad \sum_{v \in V} \sum_{j \in N'} l_{ji}^{ri,v} = p^{ri}; \quad \forall r \in N, \forall i \in N' \quad (6.14)$$

$$\sum_{v \in V} \sum_{j \in N'} l_{ij}^{is,v} = p^{is}; \quad \forall s \in N, \forall i \in N' \quad (6.15)$$

$$\sum_{j \in N'} l_{ji}^{rs,v} = \sum_{j \in N'} l_{ij}^{rs,v}; \quad \forall i \in N', \forall r, \forall s \in N \setminus \{i\}, \forall v \in V \quad (6.16)$$

$$l_{i0}^{rs,v} = 0 \text{ and } l_{0j}^{rs,v} = 0; \quad \forall i \in N', \forall r \in N, \forall s \in N, \forall v \in V \quad (6.17)$$

$$Q * \sum_{t \in T} a_{ijt} \lambda_t \geq \sum_{r \in N} \sum_{s \in N} l_{ij}^{rs,v}; \quad \forall i \in N', \forall j \in N', \forall v \in V \quad (6.18)$$

$$\sum_{t \in T} \lambda_t = 1; \quad (6.19)$$

$$l_{ij}^{rs,v} \geq 0; \quad \forall i \in N, \forall j \in N, \forall r \in N, \forall s \in N, \forall v \in V \quad (6.20)$$

$$\lambda_t \geq 0; \quad \forall t \in T \quad (6.21)$$

In this program the variables are $l_{ij}^{rs,v}$ and λ_t . The first one is defined as in MIP (6.1)-(6.12). The second one, λ_t , is a continuous non-negative variable associated with each deployment of trucks t as previously defined. Constraints (6.14)-(6.17) and (6.20) have the same meaning as in MIP (6.1)-(6.12). Constraint (6.18) relates to the deployments of trucks with the flow of commodities on each truck. Constraints (6.19) and (6.21) are the convexity constraints required to use convex combinations to obtain each x_{ij} .

Notice that the MP presented above is a LP. However, generating the complete set of deployments T is not practical. Therefore, column generation is used to work with a restricted number of variables. Hence, rather than working with the complete MP a restricted MP (RMP) is used. Variables (or columns) are generated iteratively by a subproblem (Sub-P) and controlled by reduced cost of the RMP. The exact procedure is presented in the following subsection.

6.3.3 Sub problem (Sub-P)

As presented above, the use of all the variables in the MP is avoided by using a restricted master problem. Variables associated with columns of this LP are generated as needed through column generation. In column generation, the RMP is solved with an initial set of variable that might include costly dummy columns. Then, the reduced cost \bar{c} associated with this solution is checked. If there exists a column such that $\bar{c} < 0$, this column is added to the RMP –which is solved again. Otherwise, the solution of the RMP is equivalent to the solution of the MP. Recall that this is valid only for the MP that is a

linear relaxation of the original problem and not a solution of the original MIP. Notice that the reduced cost of the MP is given by

$$\bar{c} = \sum_{v \in V} \sum_{(i,j) \in A} x_{ij}^v * (c_{ij} - \pi_{ij}) - \pi_0 \quad (6.22)$$

Where π_{ij} are the dual variable associated with the set of constraints (6.18) –each of them associated with an arc $(i,j) \in A$ – and π_0 is the dual variable associated with the convexity constraint (6.19). Hence, a negative value of \bar{c} can be found minimizing the following IP.

$$\min \quad \sum_{v \in V} \sum_{(i,j) \in A} x_{ij}^v * (c_{ij} - \pi_{ij}) - \pi_0 \quad (6.23)$$

$$\text{s.t.} \quad \sum_{v \in V} \sum_{j \in N} x_{ij}^v = 1; \quad \forall i \in N' \quad (6.24)$$

$$\sum_{j \in N} x_{0j}^v = 1; \quad \forall v \in V \quad (6.25)$$

$$\sum_{j \in N} x_{ji}^v = \sum_{j \in N} x_{ij}^v; \quad \forall i \in N, \forall v \in V \quad (6.26)$$

$$\sum_{i \in M} \sum_{j \in M} x_{ij}^v \leq |M| - 1; \quad \forall M \subset N', \forall v \in V \quad (6.27)$$

$$x_{ij}^v \in \{1,0\}; \quad \forall i \in N, \forall j \in N, \forall v \in V \quad (6.28)$$

IP (6.23)-(6.28) is a vehicle routing problem (VRP), which is notoriously a NP-Hard problem. Although solving to optimality is not critical for the size of the instances considered in this work, the amount of resources required to solve slightly larger instances is cumbersome. Therefore, the development and implementation of heuristics to efficiently approximate the Sub-P is suggested as a future improvement of the algorithm.

6.3.4 Branch-and-price (B&P)

A summary of the B&P algorithm is presented in Figure 6.3.

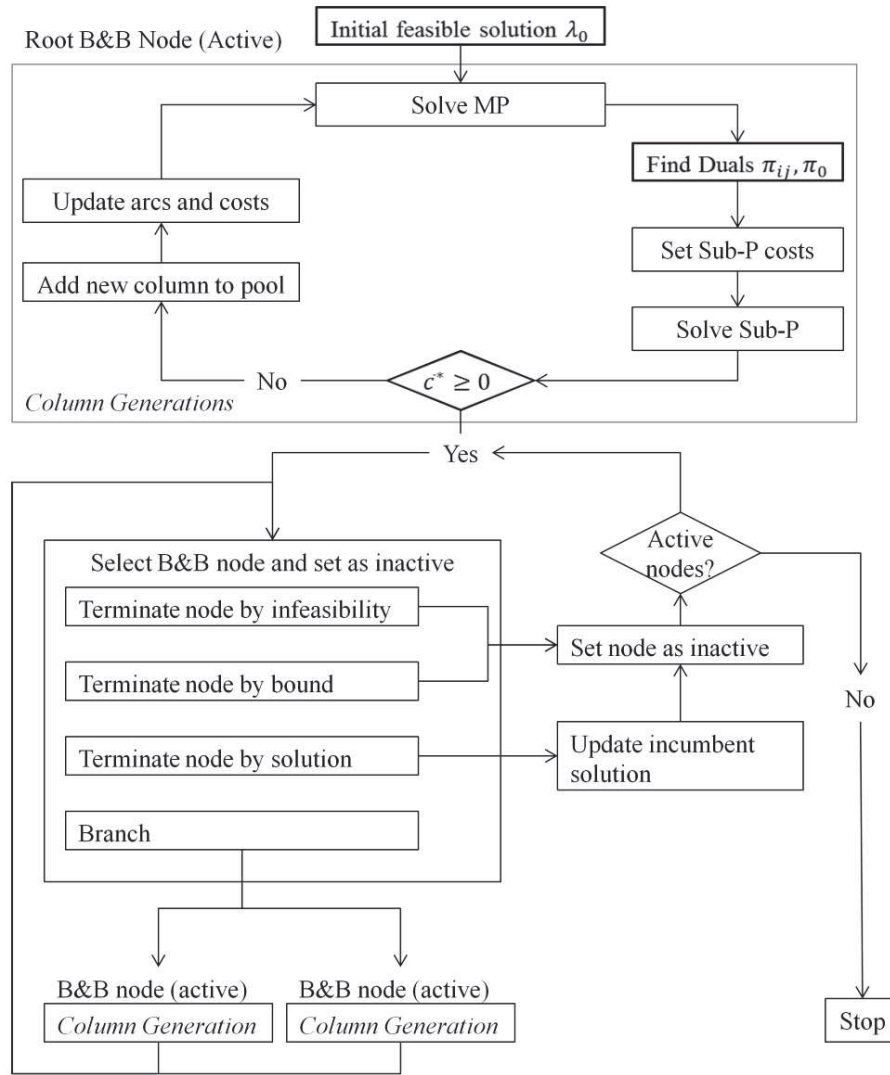


Figure 6.3 Branch-and-Price (B&P) Framework

In this figure, first a B&B node is generated and denominated as root of the tree. This node is initialized with an initial costly dummy variable that initializes the generation of columns. As presented in the previous subsections, the column generation procedure solves the RMP, constructs the reduced cost function \bar{c} with the duals of the MP (π_{ij} and

π_0), and solves the Sub-P. If there exists a deployment $t \in T$ such that the minimum of \bar{c} , \bar{c}^* , is lesser than zero, then this deployment is added to the pool of columns and the previous RMP is modified to consider the new generated column, with its corresponding costs and scope, and the RMP is solved again. The procedure continues until a reduced cost that is greater than or equal to zero is found. Once the column generation procedure stops in a B&B node the solution is analyzed. If it is not possible to find a feasible solution for that instance of the problem, then the node is terminated. If the node solution is greater than the incumbent solution, the node is terminated. If the node solution is lesser than the incumbent solution and integer the node is terminated but the incumbent solution is replaced by this one. Finally, if the node solution does not hold any of these conditions, the node is branched and two new instances of the RMP are generated as two new nodes in the B&B tree. In one node, one arc or deployment variable is set to zero. In the other one, the same variable is set equal to one. Then the column generation is solved in each of these nodes again and the algorithm continues checking whether these nodes are terminated or branched. The algorithm stops when there are no more nodes to terminate or branch and the optimal solution is returned.

6.3.5 Acceleration strategies

Originally a depth-first search is implemented to explore solutions in the B&B tree. However, the computational time with this procedure is high because finding an initial incumbent solution (feasible and integer), that represents an upper bound to the optimal solution, takes a reasonable amount of time. Then, fathoming other nodes to increase the lower bound before finding the optimal solution consumes the remaining time.

To save time in the initial search Strategy 1 is proposed. Here, the algorithm is initialized with two initial solutions: the costly initial solution used before λ_0 , and an initial feasible solution to the problem λ_1 associated to a feasible deployment $t = 1 \in T$. This deployment is found connecting the depot with any node that is a demand origin, then connecting to its corresponding destination, then connecting to another origin not previously selected, and so on. Once all demand is covered, the deployment returns to the depot. This procedure is easily extended to multiple vehicles. After column generation in the root B&B node, if this node is branched, the search proceeds to a branch associated to a link covered by $t = 1 \in T$. Then, if the next B&B node is also branched, the search continues to a branch associated to a link covered by $t = 1 \in T$, and so on up to finding $\lambda_1 = 1$. After this, the depth first search continues normally.

Although Strategy 1 accelerates solution times, there are middle and large size instances in which computational time increases considerably and one wants to obtain the current solution and evaluate the optimality gap. However, the procedure so far rarely increases the lower bound of the solution at early stages of the algorithm. Therefore, the optimality gap is not small which is undesirable. Thus, Strategy 2 is proposed to mitigate this issue. Strategy 2 is run after $\lambda_1 = 1$ is found (from Strategy 1). Then, the node with lowest current solution is selected and fathomed. This procedure continues up to finding the optimal solution.

The numerical experiments shown in the next section demonstrate the acceleration properties of these strategies. In essence, Strategy 1 reduces computational times as compared to the deep-first search, and results from Strategy 2 are sometimes faster than those obtained merely from Strategy 1.

6.4 Numerical Results

This section presents numerical results for the formulation defined above. Figure 6.4 presents a description of the numerical example. Since a complete network is considered, traversing arcs are not drawn. On the other hand, the arrows connecting nodes represent the auctioned lanes associated to each scenario -three in total-. Each of them is associated with an amount of freight (20 or 10 units). Likewise, the depot is labeled as 0 according to the notation above. Scenario 1 presents 2 auctioned lanes, i.e., a network with 5 nodes. Scenario 2 presents 3 auctioned lanes, i.e., a network with 7 nodes. Finally, Scenario 3 presents 4 auctioned lanes, i.e., a network with 9 nodes. The matrix in Figure 6.4 presents the traversing cost between nodes. Each scenario is tested with a number of trucks lesser than or equal to the number of auctioned lanes. Likewise, three different values are considered for the capacity of the trucks, i.e., 20, 40, and, 50.

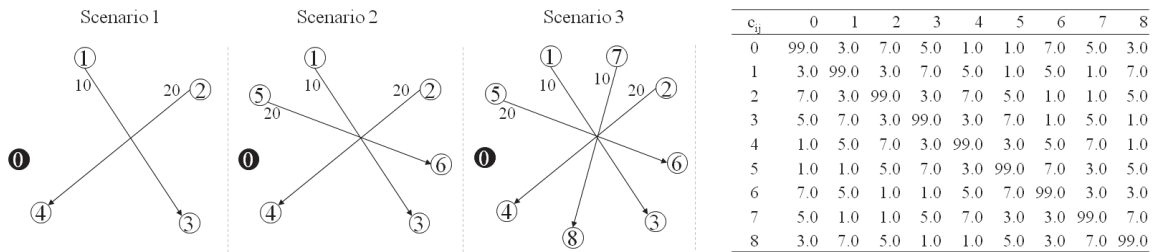


Figure 6.4 Numerical Example

The B&P algorithm is coded in Java. Several classes are created to set up the problem, manipulate the deployments in the transportation network, build the B&B tree with its corresponding nodes, and transfer information between the MP and the Sub-P. Likewise, ILOG CPLEX is called from the Java code to solve the LP associated with the MP and the IP associated with the Sub-P. An initial expensive solution λ_0 is used to initialize the algorithm, where $t = 0$ is a dummy deployment visiting all the arcs.

Table 6.2. Numerical results LTL bids.

$ N $	$ V $	Q	Min.	CostDeployment	Bundles	Time (sec)			
						Deep-first search	<i>Strategy 1</i>	<i>Strategy 2</i>	Gap (%)
5	1	50	13	0-1-2-3-4-0	{(1,3),(2,4)}	0.203	0.171	0.313	0.0
5	1	40	13	0-1-2-3-4-0	{(1,3),(2,4)}	0.188	0.188	0.406	0.0
5	1	20	21	0-1-3-2-4-0	{(1,3),(2,4)}	1.640	0.734	0.531	0.0
5	2	50	30	0-1-3-0-2-4-0	{(1,3)}, {(2,4)}	1.063	1.125	0.265	0.0
5	2	40	30	0-1-3-0-2-4-0	{(1,3)}, {(2,4)}	1.094	1.078	0.203	0.0
5	2	20	30	0-1-3-0-2-4-0	{(1,3)}, {(2,4)}	0.891	0.672	0.235	0.0
7	1	50	11	0-5-1-2-6-3-4-0	{(1,3),(2,4),(5,6)}	0.359	0.234	0.281	0.0
7	1	40	15	0-5-1-6-2-3-4-0	{(1,3),(2,4),(5,6)}	2.609	8.062	1.718	0.0
7	1	20	31	0-5-6-1-3-2-4-0	{(1,3),(2,4),(5,6)}	1.937	4.688	5.859	0.0
7	2	50	28	0-2-4-0-5-1-6-3-0	{(2,4)}, {(1,3),(5,6)}	23.124	13.469	4.390	0.0
7	2	40	28	0-2-4-0-5-1-6-3-0	{(2,4)}, {(1,3),(5,6)}	16.734	16.109	4.781	0.0
7	2	20	32	0-1-3-0-5-6-2-4-0	{(1,3)}, {(2,4),(5,6)}	7.390	7.109	6.000	0.0
7	3	50	45	0-1-3-0-2-4-0-5-6-0	{(1,3)}, {(2,4)}, {(5,6)}	15.344	3.985	1.812	0.0
7	3	40	45	0-1-3-0-2-4-0-5-6-0	{(1,3)}, {(2,4)}, {(5,6)}	14.203	13.406	1.813	0.0
7	3	20	45	0-1-3-0-2-4-0-5-6-0	{(1,3)}, {(2,4)}, {(5,6)}	5.484	3.719	1.125	0.0
9	1	50	13	0-5-1-7-6-2-3-8-4-0	{(1,3),(2,4),(5,6),(7,8)}	19.203	37.265	12.188	0.0
9	1	40	13	0-5-1-7-6-2-3-8-4-0	{(1,3),(2,4),(5,6),(7,8)}	7.094	53.656	10.531	0.0
9	1	20	31	0-5-6-7-1-8-3-2-4-0	{(1,3),(2,4),(5,6),(7,8)}	53.312	103.359	55.406	0.0
9	2	50	26	0-2-4-0-5-1-7-6-3-8-0	{(2,4)}, {(1,3),(5,6),(7,8)}	574.012	219.905	113.172	0.0
9	2	40	26	0-2-4-0-5-1-7-6-3-8-0	{(2,4)}, {(1,3),(5,6),(7,8)}	383.779	214.186	174.281	0.0
9	2	20	30	0-1-7-3-8-0-5-6-2-4-0	{(1,3),(7,8)}, {(5,6),(2,4)}	5.812	36.406	130.657	0.0
9	3	50	43	0-2-4-0-5-1-6-3-0-7-8-0	{(2,4)}, {(1,3),(5,6)}, {(7,8)}	2148.677	254.654	397.782	0.0
9	3	40	43	0-2-4-0-5-1-6-3-0-7-8-0	{(2,4)}, {(1,3),(5,6)}, {(7,8)}	1267.945	270.67	413.016	0.0
9	3	20	43	0-1-7-3-8-0-2-4-0-5-6-0	{(2,4)}, {(1,3),(7,8)}, {(5,6)}	205.436	91.984	138.625	0.0
9	4	50	60	0-1-3-0-2-4-0-5-6-0-7-8-0	{(1,3)}, {(2,4)}, {(5,6)}, {(7,8)}	692.870	91.375	58.084	0.0
9	4	40	60	0-1-3-0-2-4-0-5-6-0-7-8-0	{(1,3)}, {(2,4)}, {(5,6)}, {(7,8)}	503.496	101.702	77.581	0.0
9	4	20	60	0-1-3-0-2-4-0-5-6-0-7-8-0	{(1,3)}, {(2,4)}, {(5,6)}, {(7,8)}	260.092	59.71	39.563	0.0

Table 6.2 presents the numerical results for this example. Looking at deployment costs, it is observed that the total system cost increases when more trucks are deployed and when the capacity of these trucks is low. This supports in-vehicle consolidation as a cost reduction strategy where the assets of the carriers (trucks) are used efficiently. However, it should be noticed that this conclusion is valid only in contexts where dynamic features are not considered, e.g., time dependent demand, time windows, and deadlines, which will be discussed in the following section.

From the algorithmic efficiency perspective, computational time increases with the number of nodes in the network as expected. Additionally, by comparing instances with high and low truck capacities it is observed that the former tend to require higher computational effort than the second one. This is expected because high capacities are related to more consolidation options that have to be systematically fathomed in the B&B tree. Likewise, it shows how incorporating consolidation is computationally more challenging than considering just TL operations. On the other hand, it is observed that Strategies 1 and 2 accelerate the algorithm as compared to a merely deep-first search strategy. For this particular example it is observed that Strategy 1 is slightly faster than Strategy 2. However, the value of Strategy 2 is higher in large instances where no optimal solution can be reached but a good approximation with low optimality gap is acceptable.

The competitiveness of consolidated (LTL) bids over the non-consolidated (TL) ones is illustrated with an extension of Scenario 3 (Figure 6.4), where the same number of bundles is obtained considering TL operations. A simple way to model TL behavior in the current framework is setting each demand lane equal to the capacity of the truck. Thus, the results of running this scenario using Strategy 2 are presented in Table 6.3.

Table 6.3. Numerical results TL bids (Scenario 3)

$ N $	$ V $	Min. Cost	Deployment	Bundles	Time (sec)	Gap (%)
9	1	43	0-1-3-2-4-5-6-7-8-0	$\{(1,3),(2,4),(5,6),(7,8)\}$	14.000	0.00
9	2	42	0-1-3-2-4-0-5-6-7-8-0	$\{(1,3),(2,4)\}, \{(5,6),(7,8)\}$	25.266	0.00
9	3	47	0-1-3-0-5-6-2-4-0-7-8-0	$\{(1,3)\}, \{(2,4),(5,6)\}, \{(7,8)\}$	113.172	0.00
9	4	60	0-1-3-0-2-4-0-5-6-0-7-8-0	$\{(1,3)\}, \{(2,4)\}, \{(5,6)\}, \{(7,8)\}$	78.188	0.00

Next, the optimal bundles obtained for the LTL carrier in Scenario 3 (Figure 6.4) are compared to those that would be submitted if TL operation is assumed instead. Likewise,

the optimal bundles obtained for TL operation are re-estimated considering in-vehicle consolidation (LTL). The results of this experiment are presented in Table 6.4, where the first column indicates the type of operation for which the bundle in the second column is optimal. The following columns indicate for each type of operation the optimal deployment to serve the demand in the bundle, its total cost, and cost per lane. It is observed that the total cost and cost per lane for the LTL operation are always less than or equal to the corresponding costs for the TL carrier. Thus, LTL carriers considering in-vehicle consolidation can submit bundles with prices slightly lower to the operational costs of TL carriers –which increases their probability of winning the auctioned lanes– and perceive considerable profits. These profits are computed in the last column of Table 6.4. Notice that the difference is more pronounced when fewer vehicles are used. This is because as the number of vehicles serving the whole network increases there are less possibilities of consolidation and, therefore, the LTL operation is very similar to the TL one (When the number of trucks equals the number of lanes, costs for TL and LTL are equal). This trend also occurs when the capacity of the vehicles is low, as observed for several instances in Table 6.2 where the capacity of the trucks is reduced to 20 units and the resulting deployment follow a TL-type of operation (direct shipments).

Table 6.4. Comparison between LTL and TL bundles

Opt. for	Bundle	No. lanes	LTL operation			TL operation			LTL min margin
			Deployment	Total cost	Cost per lane	Deployment	Total cost	Cost per lane	
LTL	{(1,3),(5,6),(7,8)}	3	0-5-1-7-6-3-8-0	11.00	3.67	0-5-6-1-3-7-8-0	35.00	11.67	24.01
LTL	{(1,3),(5,6)}	2	0-5-1-6-3-0	13.00	6.50	0-5-6-1-3-0	25.00	12.50	12
TL	{(1,3),(2,4)}	2	0-1-2-3-4-0	13.00	6.50	0-1-3-2-4-0	21.00	10.50	8
TL	{(5,6),(7,8)}	2	0-5-7-6-8-0	13.00	6.50	0-5-6-7-8-0	21.00	10.50	8

Opt. for	Bundle	No. lanes	LTL operation			TL operation			LTL min margin
			Deployment	Total cost	Cost per lane	Deployment	Total cost	Cost per lane	
TL	{{(5,6),(2,4)}}	2	0-5-2-6-4-0	13.00	6.50	0-5-6-2-4-0	17.00	8.50	4
TL/LTL	{{(1,3),(2,4),(5,6),(7,8)}}	4	0-5-1-7-6-2-3-8-4-0	13.00	3.25	0-1-3-2-4-5-6-7-8-0	43.00	10.75	30
TL/LTL	{{(1,3)}}	1	0-1-3-0	15.00	15.00	0-1-3-0	15.00	15.00	0
TL/LTL	{{(2,4)}}	1	0-2-4-0	15.00	15.00	0-2-4-0	15.00	15.00	0
TL/LTL	{{(5,6)}}	1	0-5-6-0	15.00	15.00	0-5-6-0	15.00	15.00	0
TL/LTL	{{(7,8)}}	1	0-7-8-0	15.00	15.00	0-7-8-0	15.00	15.00	0

In summary, the numerical examples show that -under the conditions assumed for the problem above- the bids submitted by a LTL carrier that considers in-vehicle consolidation can be priced below or at the same price of bundles submitted by TL carriers. Interestingly, LTL carriers can perceive considerable profits when several shipments are consolidated in few trucks while TL carries would be bidding at a breakeven point, where operational cost equals price. Furthermore, the shipper conducting the auction can reduce its procurement expenditure by receiving consolidated bids with more favorable prices.

The following section summarizes the findings of this research, discusses about its limitations, and provides interesting research directions to be approached in posterior works.

6.5 Conclusions

This Chapter quantifies the benefits of considering in-vehicle consolidation –a behavior suitable for LTL firms- in the construction of bids that can be submitted to a combinatorial auction for the procurement of freight transportation services. This strategy is compared with the TL bids (direct shipments) which have been the only strategy considered by carriers participating in these auctions and past research on bidding

advisory models. Thus, an m-PDVRP model is presented to find the combination of bundles that minimizes the system cost associated to a deployment of vehicles in the network auctioned by the shipper and a branch-and-price algorithm is presented to find optimal solutions to the problem. The numerical results show that consolidated (LTL) bids dominate the non-consolidated (TL) ones.

Specifically, it is shown that the cost of serving a bundle with in-vehicle consolidation is always less than or equal to the cost of serving it with direct shipments. Thus, LTL carriers can submit bids with prices that are less than or equal to the costs of TL carriers for the same bundles and getting profits while TL carriers could just reach the breakeven point. This characteristic is better appreciated in bundles where several lanes are consolidated in one truck, which can be done using large trucks with consolidation capabilities, e.g., STAA double trailers, rocky mountain doubles, turnpike doubles, and triple trailers. On the other hand, shippers can benefit from this behavior by receiving low price bids that can potentially reduce their procurement costs.

It is important to highlight that the strategy considered in this Chapter only covers in-vehicle consolidation, which does not apply for typical LTL firms where shipments are consolidated in facilities that are strategically located over the transportation network, e.g., terminals, or hubs. Hence, this strategy is closer to a hybrid approach that incorporates the flexibility and economies of scope of TL shipments with the economies of scale and density encouraged by in-vehicle consolidation. Differentiating these two types of consolidation is important because LTL shipments that are consolidated in facilities are associated with high transportation times, which is not beneficial for shippers/commodities with high value of time, and is the main reason to prefer TL

shipments. However this hybrid approach does not require consolidation and sorting in facilities since shipments are directly consolidated inside vehicles, e.g., plugging additional trailers, or adding containers. Although serving several shipments with one truck represents higher delivery times than direct shipments, these times are not as high as a pure LTL approaches with consolidation in facilities. Nevertheless, additional research is required to understand how increased travel times and low prices affect the procurement decision of the shipper. This can be approached using econometric techniques, e.g., discrete choice models, to obtain marginal rates of substitution between price and time that can be incorporated in the construction of optimal bids.

CHAPTER 7. PRICING AND BUNDLING LESS THAN TRUCKLOAD SERVICES: STOCHASTIC DEMAND

7.1 Introduction

Based on the successful implementation of truckload (TL) combinatorial auctions (CA), this Chapter combines available information to derive the taxonomy of a less-than-truckload (LTL) CA. Then, a bidding advisory model for LTL CA that accounts for stochastic demand, designated as BM \circ LS, is proposed. This model is the first bidding advisory model for LTL CA and also improves limitation of TL models by (1) using a value-based pricing approach that properly handles the pricing rules of TL CAs, (2) segmenting demand such that the carrier can specify the maximum lane flow that is willing to serve in each bundle, and (3) incorporating demand uncertainty. A two-stage minimum-cost flow problem with stochastic capacity and demand (MCFSCD) is embedded into BM \circ LS and solved using a series of network transformations to formulate its deterministic equivalent (DE) and solve it as an efficient minimum-cost flow (MCF) problem. A numerical experiment illustrates the application of BM \circ TS.

The first contribution of the Chapter is combining available information to derive the taxonomy of LTL CA. Furthermore, the comprehensive literature review in Subsection 1.2.3 shows that there is no bidding advisory model for LTL CA. This gap is narrowed by

BM ◦ LS (Bidding Model for LTL CA with Stochastic demand), an algorithmic framework that additionally improves limitations of current TL bidding advisory models by (i) bundling based on value-based pricing and properly handle managing the pricing rules of CA, (ii) segmenting demand so that the maximum lane flow that the carrier is willing to serve is explicitly defined in each bid, and (iii) incorporating demand uncertainty in the construction of bundles.

This Chapter is organized as follows. Section 7.1 motivates the problem. Section 7.2 provides a comprehensive literature review that highlights the gap on research and motivates the directions taken in the development of BM◦LS. Section 7.3 expands the concepts of LTL CA, LTL systems, and freight stochastic demand, which has to be mastered before properly defining and formulating the LTL bidding problem in Section 7.4. Section 7.5 presents BM◦LS, an algorithmic framework to solve this problem, which is based in a novel algorithm to assign demand into the LTL network while accounting for uncertainty. Section 7.6 illustrates the implementation of BM◦LS with a numerical example. Finally, Section 7.7 concludes the Chapter with a summary of this research.

7.2 Literature review

This section presents a comprehensive literature review of LTL systems. This review shows that a work addressing the bidding problem for LTL carriers in LTL CA is missing in literature, a gap narrowed by the current work.

LTL systems have been widely studied from the service design perspective. Crainic (2000) reviews service network design studies, many of them related to LTL operations. Pioneering works (Powell 1986, Powell and Sheffi, 1983 and 1989) developed frameworks for LTL network design and implemented them in commercial settings (Braklow et al. 1992). These flow-based approaches introduce important LTL concepts (e.g., *load plans*, terminal definition, direct services, levels of service, etc.) and methods. Keaton (1993) combine service network design concepts with facility location to demonstrate the benefits of economies of density for LTL carriers. Jarrah et al. (2009) develops a similar network design problem that is solved using an original sequential approach. These works are formulated to address the challenging strategic planning faced by LTL carriers.

The operational LTL problems offer a high level of complexity and are even more challenging. For example, Rieck and Zimmermann (2009) use a vehicle routing approach that accommodate multiple constraints to study cooperation between middle size LTL carriers in Europe. Estrada and Robusté (2009) propose a method for LTL long-haul routing with capacitated distribution centers and time-constrained shipments. Barcos et al. (2010) approach different details of LTL network design problem that add more complexity to the models in earlier years. As a common trait, these works take advantage of heuristic approaches to solve these complex problems, e.g., meta-heuristics like local search, taboo search, ant colony, among others, are popular.

A significant amount of work in LTL modeling has been conducted in the last few years by Lin and co-authors. Lin (2001) studies LTL freight routing in a cost minimization framework using an explicit enumeration approach that is similar to

branch-and-bound. Lin (2004) investigates the LTL load planning with uncertain demands using two-stage stochastic programming. Lin and Chen (2004) explore cases when *load plans* can incorporate two paths between different terminals in the LTL network. However, common practice is assuming just one. Lin et al. (2009) present a good taxonomy of the LTL network and propose a pricing model for LTL services that assume (i) that demand can be estimated as a continuous and invertible function of price, (ii) revenue follows a concave continuous function, and (iii) capacities are fixed in the network.

Other topics related to LTL research include collaboration (which has received significant attention by several authors e.g., Hernández and Peeta, 2011, Hernández et al. 2011, Hernández et al. 2012, Nadarajah et al. 2013, Xu et al. 2009), econometric pricing (Özkaya, E et al. 2010), assignment of drivers (Erera 2008), benefits of LTL operations for reductions in emissions (Clausen et al. 2012), inventory management related to LTL systems (Buijs et al. 2014, Banerjee, 2009), pickup-and-deliveries at end of lines (EOLs) (Barnhart and Kim, 1995), and real time decisions (Hejazi et al. 2007).

However, no work approaching the bidding problem for LTL carriers in CA is found in literature. This problem has been mainly explored from a TL perspective (Song and Regan, 2003 and 2005, Wang, and Xia, 2005, Lee et al. 2007) but these works suffer of the following issues: (i) pricing is not properly addressed using value-based frameworks, (ii) demand segmentation within bids submitted to the CA is not allowed, and (iii) uncertainty is not considered.

Meaningful conclusions are obtained from this review. LTL systems can be modeled using network flow approaches if they are properly defined. Heuristic approaches are

commonly required to solve these complex problems. Uncertainty has been scarcely incorporated in these problems but can be approached using DE approaches. Operational constraints, e.g., *load plans*, are critical in the operation of LTL systems and have to be considered to obtain realistic results. A bidding model for LTL CA is missing in literature. Although developing the first model in this context is a significant contribution per se, addressing the limitations in previous TL bidding advisory model adds considerable value to this work.

Given this review and conclusions, the following sections provide preliminary concepts to deeply understand LTL CA, LTL systems, freight demand uncertainty, and, furthermore, develop the robust and efficient algorithmic framework proposed in this work (BM \circ LS).

7.3 Preliminaries

Preliminary concepts have to be reviewed and defined before to properly define and formulate the bidding problem approached in this research.

This section is organized as follows. Subsection 7.3.1 clarifies the context of an LTL CA. Subsection 7.3.2 reviews the operational characteristics of LTL systems. Finally, Subsection 7.3.3 shows the importance of considering stochastic demand in freight transportation and how this affects the bidding problem faced by LTL carriers.

7.3.1 LTL combinatorial auctions (CA)

There is a considerable amount of evidence in literature about the implementation of TL CA (De Vries, and Vohra, 2003, Elmaghraby, and Keskinocak, 2004, Ledyard et al.

2002, Moore et al. 1991, Sheffi, 2004). However, little is known about how these auctions are conducted in the LTL context. In practice, there are several websites conducting online freight auctions for both TL and LTL, e.g. Cargo Auctions (2011), and Freight Brokers USA (2014). They offer the possibility for shippers to post lanes that require TL or LTL transportation and specifying pickup/delivery locations, weight, and other requirements, e.g., special equipment. However these places do not give the possibility for carriers to bundle demand. Although, carriers can bid for multiple lanes that would work economically when served together, the risk of losing a subsets of them exists and is potentially harmful for its operation. Following this idea, software development companies, e.g., SciQuest (2014) (which acquired CombineNet), SMC3 (2006), and DeltaBid (2014), offer solutions to develop business-to-business (B2B) procurement applications, e.g., requests for proposals (RFP), request for quotes (RFQ), and request for information (RFI). Thus, LTL CA are offered as a type of RFQ. Although the service is openly publicized, specific information about the details of such implementations is not available.

On the other hand, scant documentation about these auctions is available in literature. To the best of authors' knowledge, only Achermann et al. (2011), and Dai et al. (2014) approach LTL CA as mechanisms to distribute lanes among cooperative LTL carriers. However, these academic exercises are theoretical and do depict the shipper/carrier interaction, i.e., only carrier/carrier interaction is considered.

Although shippers conduct LTL CA in practice, this market interaction is not properly illustrated in literature. A formal definition of LTL CA is presented next.

Let a lane be the volume of shipments per unit of time between an origin-destination (OD) pair. Their small size and supply-chain context make them suitable to be transported by LTL carriers. A shipper requires transportation services for several lanes and conducts a LTL CA to collect quotes for combinations of them. There is a maximum price that the shipper is willing to pay for each lane, i.e., reservation price. This is a reverse auction where the auctioneer is a shipper that procures transportation services, and bidders are the carriers offering them. Auctioned items are freight lanes. Several LTL carriers are invited to the auction and the following information is communicated to them: lane origins, destinations, volumes (shipments per unit of time), and dimensions. The carriers analyze this information and construct a set of bundles. Each bundle includes a combination of shipments desired to be served. A unique price per unit of weight is charged to all lanes in the bundle. Dimensional weighting is used to account for critical dimensions of the shipments. Furthermore, the carriers specify the maximum volume willing to serve for each lane in the bundle. After collecting all bids, in a single-round LTL CA, the shipper solves the winning determination problem (WDP) to find the combination of bundles that covers all lanes and represents the lowest procurement cost. Then, the right to serve the lanes in the winning bids is assigned to the corresponding carriers. In a multiple-round LTL CA, information about the best prices on each lane is communicated back to the carriers and they prepare new bids. This loop repeats for 2 or 3 iterations. Usually, there is a post-negotiation process where specific certain lanes are re-negotiated in order to maintain behavioral preferences of the shipper and other business constraints. The following notation is used to formally represent sets and parameters in the LTL CA.

Sets and indexes:

D set of lanes auctioned in the auction.

od index related to an OD pair. $od \in D$

B set of bids submitted to the auction.

b index associated with each bid. $b \in B$.

β^b set of lanes included in bid $b \in B$. $\beta^b \subset D$.

Parameters:

q^{od} (weight/time) lane flow from origin o to destination d , where $od \in D$.

p^{od} (\$/weight) unitary reservation price per weight for lane $od \in D$.

y^{bod} (weight/time) maximum amount of flow that the carrier is willing to serve for lane $od \in D$ as part of bid $b \in B$.

p^b (\$/weight) unitary price per weight charged to all lanes included in bid $b \in B$.

Preparing bids for LTL CA is a challenging tasks faced by LTL carriers. These agents should properly integrate the information communicated in the LTL CA to their current operations in order to construct profitable and attractive bundles. So, understanding the operation of LTL carriers is critical to propose an assertive bidding advisory model.

7.3.2 Less-than-truckload (LTL) systems

The introduction provided in Subsection 1.1.2 is complemented with the following definition of LTL systems.

A LTL carrier operates over a well-defined network that is currently serving a number of clients. *Load Plans* are already defined so there is a pre-specified OD path between every pair of terminals in the network with acceptable levels of service, i.e.,

acceptable delivery times. However, there are several links where trucks are not used to full capacity. Likewise, some terminals are underutilized. In an LTL CA, the carrier seeks to properly match such unused capacities with the lanes communicated by the shipper, and, therefore, maximizing profits by loading unutilized assets. The operational costs for LTL carrier are: transportation and terminal handling costs. Revenues come from prices charges to the shipments served.

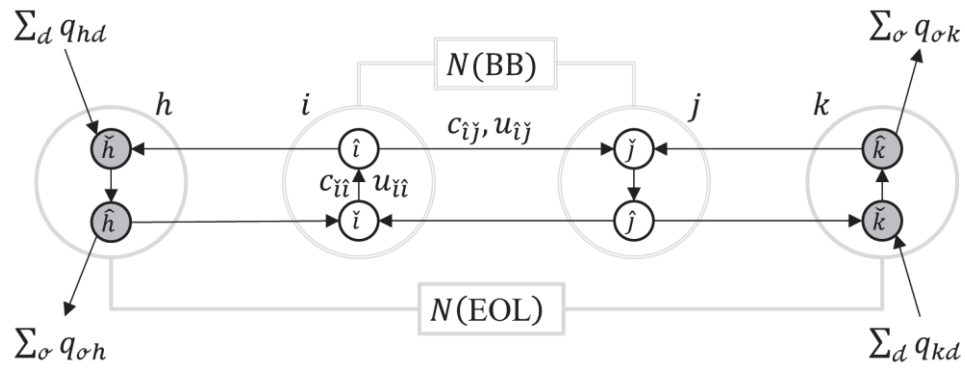


Figure 7.1 Formal representation of the LTL network.

The notation below is used to formally represent sets and parameters describing the LTL network and its operation. Figure 7.1 illustrates some of these concepts. Without loss of generality, any terminal i is represented as an arc $(\tilde{i}, \hat{i}) \in A$, where node $\tilde{i} \in N$ (with accent mark pointing into the node index) indicates shipments that enter the terminal, and node $\hat{i} \in N$ (with accent pointing out of the node index) indicates shipments that depart from it. Furthermore, a movement between terminals (i, j) is executed between the corresponding nodes $(\hat{i}, \tilde{j}) \in A$. Finally, shipments originated in a region served by an EOL enter the LTL network through the an entering node $\tilde{i} \in N(\text{EOL})$, and shipment delivered in such region exit the network from the corresponding departing node $\hat{i} \in N(\text{EOL})$.

Sets:

$G(N, A)$ LTL network composed by a set of terminals N and a set of arcs A connecting them.

N set of nodes representing terminals in the LTL network. $N = N(\text{EOL}) \cup N(\text{BB})$.

$N(\text{EOL})$ set of nodes related to EOL terminals.

$N(\text{BB})$ set of nodes related to BB terminals.

A set of directed arcs representing connections between or within terminals, i.e., $(\hat{i}, \hat{j}) \in A$ and $(\check{i}, \hat{i}) \in A$ respectively.

Parameters:

$c_{\hat{i}}$ (\$/weight) unitary handling cost for terminal i represented by the terminal arc $(\check{i}, \hat{i}) \in A$.

$u_{\hat{i}}$ (weight/time) unused capacity in terminal arc $(\check{i}, \hat{i}) \in A$.

$c_{\hat{i}\hat{j}}$ (\$/weight) unitary cost for movements between terminals in the transportation arc $(\hat{i}, \hat{j}) \in A$.

$u_{\hat{i}\hat{j}}$ (weight/time) unused capacity in transportation arc $(\hat{i}, \hat{j}) \in A$.

$p^{\check{i}\hat{j}}$ (\$/weight) unitary price per weight charged to shipments originated in the region served by EOL i and delivered in the region served by EOL j , i.e., price for a movement from $\check{i} \in N(\text{EOL})$ to $\hat{j} \in N(\text{EOL})$. Notice that the carrier can only bid for lanes $od \in D$ such that o and d are associated to EOLs in its network, e.g., i and j respectively. Therefore, and without loss of generality, let $o = \check{i} \in N(\text{EOL})$ and $d = \hat{j} \in N(\text{EOL})$ for every lane where this constraint applies.

The carrier is currently serving a number of customers which determines its available capacity for new shipments. However, freight demand fluctuates significantly. The question is, how can the carrier properly account for such demand uncertainty?

7.3.3 Freight stochastic demand

The preliminary insights provided in Subsection 1.1.3 are complemented with the following definitions for freight stochastic demand. The following notation is used to formally represent sets and parameters associated with freight stochastic demand.

Sets and indexes:

Ω set of scenario realizations.

ω index related to a scenario realization. $\omega \in \Omega$.

Parameters:

$u_{il}(\omega)$ (weight/time) unused capacity in terminal arc $(i, l) \in A$ for realization $\omega \in \Omega$.

ς_{il} (\$/weight) unitary handling cost for shipments directed to terminal l , represented by arc $(i, l) \in A$, when the owned facility i operates at full capacity.

$p_{il}(\omega)$ probability of having unused capacity $u_{il}(\omega)$ available in terminal arc $(i, l) \in A$ for realization $\omega \in \Omega$.

$u_{ij}(\omega)$ (weight/time) unused capacity in transportation arc $(i, j) \in A$ for realization $\omega \in \Omega$.

ς_{ij} (\$/weight) unitary transportation cost for arc $(i, j) \in A$ when owned trucks operate at full capacity.

$p_{ij}(\omega)$ probability of having unused capacity $u_{ij}(\omega)$ available in transportation arc $(i, j) \in A$ for realization $\omega \in \Omega$.

$q^{od}(\omega)$ (weight/time) lane flow from origin o to destination d for realization $\omega \in \Omega$, where $od \in D$ such that $o = \check{i} \in N(\text{EOL})$ and $d = \hat{j} \in N(\text{EOL})$.

$p^{od}(\omega)$ probability of having the amount of demand $q^{od}(\omega)$ in lane $od \in D$ for realization $\omega \in \Omega$.

Stochastic unused capacity and stochastic auctioned demand are the two main elements that introduce uncertainty to the bidding problem. These concepts are described below.

- *Stochastic unused capacity.* The LTL carrier currently serves lanes for multiple clients (shippers). Thus, many arcs in its network are operated below capacity at different levels. However, unused capacity does not remain constant over time. Instead, it fluctuates and its realization is associated to an observed probability. Thus, the carriers can determine a set of realization scenarios Ω based on its experience and observation of unused capacity (a function of demand fluctuations). For each scenario $\omega \in \Omega$ and each terminal\transportation arc in its network, $(i, j) \in A$, the carrier estimates that with a probability $p_{ij}(\omega)$ the unused capacity is $u_{ij}(\omega)$. A cautious conservative carrier would bid only for lanes that can always be fitted within the unused capacity. However, smart carrier account for such uncertainty and bid for lanes that can potentially violate capacity but represent maximized expected profits. When demand is violated, the carrier can always sub-hire another carrier or facility that will charge a unit price ς_{ij} per weight handled/transported. This is not rare in the highly competitive trucking industry characterized by excess supply (surplus).

- *Stochastic auctioned demand.* The carrier also expects demand in auctioned lanes to fluctuate as it happens to current demand. Similar to current operations, the carrier can estimate demand realization probabilities $p^{od}(\omega)$ for the amount of flow $q^{od}(\omega)$ in the lane $od \in D$ and scenario realization $\omega \in \Omega$.

At this point, all required information is available to properly define and formulate the LTL bidding problem in the next section.

7.4 LTL bidding problem definition and formulation

The LTL Bidding Problem is defined as follows. Given a LTL CA (Subsection 7.3.1) this research approaches the perspective of a specific LTL carrier (Subsection 7.3.2), which is asked to construct a set of bids B that represents the maximum expected profits where bids are optimized to account for freight demand uncertainty (Subsection 7.3.3). The Stochastic mixed integer quadratic program (SMIQP) (7.1)-(7.16) presents the mathematical formulation of this problem. Without loss of generality, arcs in the formulation below are represented as $(i, j) \in A$ to account for terminal arcs $(\check{i}, \hat{i}) \in A$, transportation arcs $(\hat{i}, \check{j}) \in A$, and OD pairs $od = \check{i}\hat{j} \in A$. However, they maintain the definitions introduced in Section 7.3. The notation for sets, variables, and parameters not introduced before is stated below.

Variables:

$y^{b,od}(\omega)$ (weight/time) maximum amount of flow the carrier is willing to serve in lane $od \in \beta^b$ included in bid $b \in B$ associated with auctioned demand scenario $\omega \in \Omega$.

$x_{ij}^{b,od}(\omega)$ (weight/time) amount of flow traversing arc $(i, j) \in A$ in the LTL network related to bid $b \in B$ for the included lane $od \in \beta^b$ in the unused-capacity scenario $\omega \in \Omega$.

$\chi_{ij}^{bod}(\omega)$ (weight/time) amount of flow traversing arc $(i,j) \in A$ outsourced to carriers/terminals offering their services over arc $(i,j) \in A$ related to the realization $\omega \in \Omega$.

p^b (\$/weight) unitary price per weight charged to all lanes included in bid $b \in B$.

δ_{ij}^b binary routing variable. $\delta_{ij}^b = 1$ if arc $(i,j) \in A$ is used to serve the lanes $od \in \beta^b$ included in bid $b \in B$ as specified in the Load Plan described by r_{ij}^{od} ; $\delta_{ij}^b = 0$ otherwise.

Parameters:

$r_{ij}^{od} \in \{0,1\}$ binary parameter that describes the load plan for each $od \in D$. $r_{ij}^{od} = 1$ if arc $(i,j) \in A$ is used in the path to deliver lane $od \in D$, $r_{ij}^{od} = 0$ otherwise.

$\bar{\Pi}$ (\$) minimum expected profit accepted for any bid submitted to the auction.

The Objective Function (7.1), subject to the Random Constraints (7.2)-(7.16), maximizes the total expected profit z of bids associated to the expected profits $\Pi^b(\omega)$ (defined in Constraint (7.2)) for realization $\omega \in \Omega$.

$$\max z = \mathbb{E}_{\omega} \left[\sum_{b \in B} \Pi^b(\omega) \right] \quad (7.1)$$

Constraint (7.2) computes the total expected profit for all bids $b \in B$ as the sum of revenues perceived by pricing the flow $y^{bod}(\omega)$ for lane $od \in \beta^b$ at an unitary price p^b for the auctioned demand realization $\omega \in \Omega$, minus the analogous sum of costs associated to the flow served by the LTL network itself $\chi_{ij}^{bod}(\omega)$ and outsourced to other carriers when there is no sufficient capacity $\chi_{ij}^{bod}(\omega)$ in each arc $(i,j) \in A$.

$$\Pi^b(\omega) = \sum_{b \in B} \left(\sum_{(o,d) \in \beta^b} \left(p^b y(\omega) - \sum_{(i,j) \in A} [c_{ij} x_{ij}^{bod}(\omega) + \varsigma_{ij} \chi_{ij}^{bod}(\omega)] \right) \right) \quad (7.2)$$

$\forall \omega \in \Omega$

Constraint (7.3) specifies that the expected profit for each individual bid should be above a profit threshold $\bar{\Pi}$.

$$\begin{aligned} \bar{\Pi} &\leq \mathbb{E}_{\omega} [\Pi^b(\omega)] \\ \forall b \in B, \forall \omega \in \Omega \end{aligned} \quad (7.3)$$

Constraint (7.4) sets bid price p^b to the lowest reservation price for lanes considered in. This makes each bid price (i) consistent with the concept of pricing for LTL CAs, (ii) equivalent to the lowest reservation price, which make cheaper for the shipper lanes with higher p^{od} , and (iii) improves over cost-based pricing which can be lower but does not consider shipper valuation.

$$\begin{aligned} p^b &\leq p^{od}, \\ \forall b \in B, \forall od \in \beta_b \end{aligned} \quad (7.4)$$

Constraint (7.5) states that the OD flow $y^{bod}(\omega)$ considered in each bid $b \in B$ cannot exceed the flow $q^{od}(\omega)$ realization for each lane posted in the auction.

$$\begin{aligned} q^{od}(\omega) &\geq y^{bod}(\omega) \\ \forall b \in B, od \in \beta^b, \forall \omega \in \Omega \end{aligned} \quad (7.5)$$

Constraints (7.6)-(7.8) are flow conservation constraints affecting each bid $b \in B$ and scenario realization $\omega \in \Omega$. Constraint (7.6) indicates that flow handled in a terminal $x_{\mathcal{O}j}^{bod}(\omega)$ and outsourced when there is no sufficient capacity $\chi_{\mathcal{O}j}^{bod}(\omega)$, where $(\mathcal{O}, j) = (\check{j}, \hat{j})$ as in Subsection 7.3.2, is equivalent to the sum of flow originated at the region served by the corresponding EOL, $y^{bod}(\omega)$, plus the sum of flow sent from other

terminals to transit in this one using carrier's unused capacity $x_{io}^{bod}(\omega)$ and outsourced $\chi_{io}^{bod}(\omega)$.

$$\sum_{d \in N: od \in \beta^b} y^{bod}(\omega) + \sum_{od \in \beta^b} \sum_{i \in N} x_{io}^{bod}(\omega) + \chi_{io}^{bod}(\omega) = \sum_{od \in \beta^b} x_{oj}^{bod}(\omega) + \chi_{io}^{bod}(\omega) \quad (7.6)$$

$$\forall b \in B, \forall \mathcal{O} \in N(EOL): \exists \mathcal{O}d \in \beta^b, \forall \omega \in \Omega$$

Constraint (7.7) specifies that for each node i that is neither an origin o nor a destination d for a lane $od \in \beta^b$ considered in bid $b \in B$, inbound and outbound flows are equivalent

$$\sum_{j \in N} x_{ji}^{bod}(\omega) + \chi_{ji}^{bod}(\omega) = \sum_{j \in N} x_{ij}^{bod}(\omega) + \chi_{ij}^{bod}(\omega) \quad (7.7)$$

$$\forall b \in B, \forall i \in N: i \neq o, d, od \in \beta^b, \forall \omega \in \Omega$$

Constraint (7.8) designates that flow handled $x_{i\mathcal{D}}^{bod}(\omega)$ and outsourced $\chi_{i\mathcal{D}}^{bod}(\omega)$ in a terminal, where $i\mathcal{D} = \tilde{i}\tilde{l}$ as in Subsection 7.3.2, is equal to the sum of flow to be delivered in the region served by the corresponding EOL, $y^{bo\mathcal{D}}(\omega)$, plus the sum of flow that transited such terminal but was not delivered $x_{\mathcal{D}j}^{bod}(\omega)$ and $\chi_{\mathcal{D}j}^{bod}(\omega)$.

$$\sum_{od \in \beta^b} x_{i\mathcal{D}}^{bod}(\omega) + \chi_{i\mathcal{D}}^{bod}(\omega) = \sum_{o \in N: o\mathcal{D} \in \beta^b} y^{bo\mathcal{D}}(\omega) + \sum_{od \in \beta^b} \sum_{j \in N} x_{\mathcal{D}j}^{bod}(\omega) + \chi_{\mathcal{D}j}^{bod}(\omega) \quad (7.8)$$

$$\forall b \in B, \forall \mathcal{D} \in N(EOL): \exists o\mathcal{D} \in \beta^b, \forall \omega \in \Omega$$

Constraints (7.9)-(7.10) properly handle the state of variable δ_{ij}^b such that it is activated or deactivate as required, i.e., $\delta_{ij}^b = 1$ or $\delta_{ij}^b = 0$ respectively. If bid $b \in B$ includes lane $od \in \beta^b$, then $y^{bod}(\omega) > 0$, Constraint (7.10) forces $\delta_{ij}^b = 1$ for the corresponding arcs in the load plan, i.e., $r_{ij}^{od} = 1$, and Constraint (7.9) forces $\delta_{ij}^b = 0$ for arcs not included in such load plan, i.e., $r_{ij}^{od} = 0$. On the other hand, if lane $od \notin \beta^b$ is not included in bid $b \in B$, then $y^{bod}(\omega) = 0$, Constraint (7.9) forces $\delta_{ij}^b = 0$ for all arcs

in load plans related to this lane. These constraint are affected by the realization of scenario $\omega \in \Omega$.

$$\begin{aligned} \delta_{ij}^b &\leq y^{bod}(\omega) r_{ij}^{od} \\ \forall b \in B, \forall od \in \beta^b, \forall (i, j) \in A, \forall \omega \in \Omega \end{aligned} \quad (7.9)$$

$$\begin{aligned} y^{bod}(\omega) r_{ij}^{od} &\leq q^{od}(\omega) \delta_{ij}^b \\ \forall b \in B, \forall i \in N: i \neq o, i \neq d, od \in \beta^b, \forall \omega \in \Omega \end{aligned} \quad (7.10)$$

Constraint (7.11) forces the sum of fractions of multi-commodity flows $x_{ij}^{bod}(\omega)$ related to bundle $b \in B$ traversing each arc in the LTL network to be less than or equal to the available unused capacity $u_{ij}(\omega)$ for the realization $\omega \in \Omega$ so that load plans are properly covered (δ_{ij}^b).

$$\begin{aligned} \sum_{od \in \beta^b} x_{ij}^{bod}(\omega) &\leq u_{ij}(\omega) \delta_{ij}^b \\ \forall b \in B, \forall i \in N: i \neq o, i \neq d, od \in \beta^b, \forall \omega \in \Omega \end{aligned} \quad (7.11)$$

Finally Constraints (7.12)-(7.15) declare variables $y^{bod}(\omega)$, $x_{ij}^{bod}(\omega)$, $\chi_{ij}^{bod}(\omega)$, p^b to be non-negative, and Constraint (7.16) declares variable δ_{ij}^b as binary.

$$\begin{aligned} 0 &\leq y^{bod}(\omega) \\ \forall b \in B, \forall od \in \beta^b, \forall \omega \in \Omega \end{aligned} \quad (7.12)$$

$$\begin{aligned} 0 &\leq x_{ij}^{bod}(\omega) \\ \forall b \in B, \forall od \in \beta^b, \forall (i, j) \in A, \forall \omega \in \Omega \end{aligned} \quad (7.13)$$

$$\begin{aligned} 0 &\leq \chi_{ij}^{bod}(\omega) \leq 1 \\ \forall b \in B, \forall od \in \beta^b, \forall (i, j) \in A, \forall \omega \in \Omega \end{aligned} \quad (7.14)$$

$$\begin{aligned} 0 &\leq p^b \\ \forall b \in B \end{aligned} \quad (7.15)$$

$$\begin{aligned} \delta_{ij}^b &= \{0, 1\} \\ \forall b \in B, \forall (i, j) \in A \end{aligned} \quad (7.16)$$

Finding an optimal solution for the SMIQP (7.1)-(7.16) is computationally expensive for several reasons. The solution of its deterministic version is computationally expensive due to the multi-commodity nature of the problem, the quadratic form of the Objective Function (7.1), the necessity to enumerate all possible bids that grows exponentially with respect to the lanes considered, and to the inherited complexity of integer programs. However, the most critical problem to find an optimal solution is related to the violations of different realizations of demand and unused capacity. Therefore, a solution procedure that accounts for these limitations and provides good quality bundles is required. BM \circ LS is a suite of algorithms proposed to account for these challenges that provides an appropriate balance between good quality bids and a computationally tractable approach. The method is presented in the following section.

7.5 BM \circ LS methodology

This section presents BM \circ LS (Bidding Model for LTL CA with Stochastic demand), which is an algorithmic framework developed to solve the problem formulated in Section 7.4. Figure 7.2 illustrates its implementation. The section is organized as follows: first the inputs, main algorithm, and outputs are described. Then additional subsections expand details for specific modules.

The inputs required to run BM \circ LS are summarized below according to the subsection where they were introduced and defined.

Inputs

Subsection 7.3.1

D set of auctioned lanes

p^{od} (\$/weight) unitary reservation price per weight for lane $od \in D$

Subsection 7.3.2

$G(N, A)$ carrier network

c_{ij} (\$/weight) unitary costs associated with each terminal/transportation arc $(i, j) \in A$.

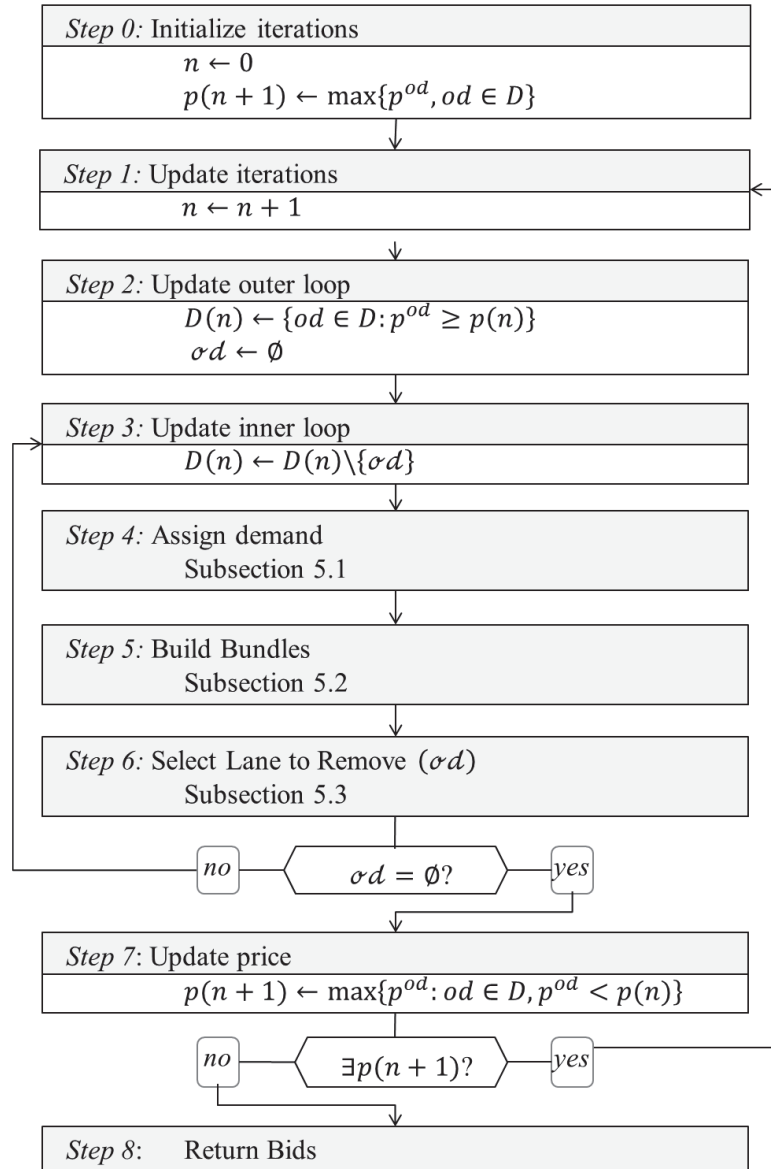


Figure 7.2 BMoLS: Main algorithm

Subsection 7.3.3

Ω set of scenario realizations. Indexed by ω

$u_{ij}(\omega)$ (weight/time) unused capacity in the terminal/transportation arc $(i, j) \in A$ of the LTL network for realization $\omega \in \Omega$.

ς_{ij} (\$/weight) unitary cost for shipments outsourced to third-parties when terminal/transportation arc $(i, j) \in A$ is operated at full capacity in the LTL network.

$p_{ij}(\omega)$ probability of having unused capacity $u_{ij}(\omega)$ available in the terminal/transportation arc $(i, j) \in A$ for realization $\omega \in \Omega$.

$q^{od}(\omega)$ (weight/time) flow on lane $od \in D$ for realization $\omega \in \Omega$.

$p^{od}(\omega)$ probability of having an amount of flow $q^{od}(\omega)$ on lane $od \in D$ for realization $\omega \in \Omega$.

In general, BM \circ LS designed based on two constituent loops, i.e., the *outer loop* and the *inner loop*. Before running such loops, the main algorithm is initialized in *Step 0* setting the counter to zero $n \leftarrow 0$ and identifying the highest reservation price for the first iteration, i.e., $p^{n+1} = p^1$.

The *outer loop* (*Steps 1-7*) analyzes lanes sequentially in a descending order with respect to their reservation prices. Each iteration is related to a price which is used to construct bids. This price decreases sequentially as iterations proceed and is the maximum price the shipper would pay for lanes in bids constructed in the current iteration. Thus, only lanes with reservation prices greater than or equal to the current one can be considered. If a lane with lower reservation price is included, then the shipper would immediately reject all lanes in the bid because it is not willing to pay such price for that lane. *Step 2* uses the current price $p(n)$ to construct an initial set of potential

lanes $D(n)$ useful for bundle generation. The *inner loop* (Steps 3-6) iteratively explores these lanes and constructs bundles. When it stops, *Step 7* seeks for the next lower price $p(n + 1)$ and a new iteration begins in *Step 1* if such price exists. On the other hand, if it is not possible to select a new price -because all of them have been explored- BM•LS stops.

But, how are bundles constructed in the *inner loop* (Steps 3-4)? This loop considers the set of potential lanes in $D(n)$ to construct bids with the same price $p(n)$ (*Step 4*). The iterative process first assigns demand to the carrier network using a loading procedure that maximizes the expected profits of lanes served conjointly and optimized for stochastic demand and capacity (*Step 4*). More details about this module are provided in Subsection 7.5.1. Lanes sharing assets in the LTL network are bundled and considered as potential bids. If the expected profit for a potential bid is greater than or equal to the acceptable profit $\bar{\Pi}$, then it is stored as a definite bid. Otherwise, it is discarded (Subsection 7.5.5). In order to explore different combinations of lanes, the lane with lowest marginal profit σd is removed from the potential lanes $D(n)$ in *Step 6*, and a new iteration of the inner loop starts from *Step 3*. This process is described in Subsection 7.5.7. When it is achieved a stage where finding a lane to remove is not possible, the *inner loop* stops and the *outer loop* continues.

The following outputs are returned when BM•LS stops.

Outputs (defined in Subsection 7.3.1)

B set of bids submitted by the LTL carrier to the LTL CA.

$\{\beta^b, y^{bod}, p^b\}$ information associated to each bid $b \in B$.

The following Subsections provide further details about the modules to Assign Demand (*Step 4* - Subsection 7.5.1), Build bundles (*Step 5* - Subsection 7.5.5), and Select Lane to Remove (*Step 6* - Subsection 7.5.7).

7.5.1 Assign Demand

This subsection describes the framework followed to assign demand in BM•LS such that the expected profits of the bundles are maximized and flows are optimized to account for demand and capacity uncertainty. The cornerstone of this module is the Minimum Cost Flow problem with Stochastic Capacities and Demand realizations (MCFSCD) (Subsection 7.5.2), which is solved efficiently applying a series of network transformations (Subsection 7.5.3) used to construct its deterministic equivalent (DE) problem and solving it as a regular Minimum Cost Flow (MCF) problem (Subsection 7.5.4).

Figure 7.3 illustrates the execution of this module. The MCFSCD takes as input a lane $od \in D(n)$ and the current price $p(n)$. Then, it outputs the profit Π^{od} associated to the desirable lane flow y^{od} and corresponding arc flows x_{ij}^{od} , where $(i, j) \in A(\Omega)$ is used to denote an arc from the a set of modified arcs introduced in Subsection 7.5.3. Although the bidding problem is a multi-commodity type of problem, a greedy algorithm is proposed to relax this limitation and take full computational advantage of the MCFSCD. The idea is based on the continuous knapsack problem where items are sorted with respect to their unitary profit and then allocated into the knapsack decreasingly up to filling it in. Thus, this module computes the unitary profits for each arc π^{od} (*Step 4.1*) based on initial MCFSCD results (*Step 4.0*) obtained by assigning each lane into the

network without interacting with others. Then, the lanes with higher unitary profits are selected iteratively. Each time a lane is selected (*Step 4.2*) it is assigned to the network (*Step 4.3*) and the resulting flows are used to reduce capacity u_{ij} for subsequent lanes (*Step 4.4*) in the modified network introduced in Subsection 7.5.3. This process continues up to analyzing all lanes with positive π_{ij} . Then, it returns the corresponding profits Π^{od} and desired flows y^{od} for the explored lanes $od \in D(n)$. The following subsections provide details for the computation of these values using the MCFSCD.

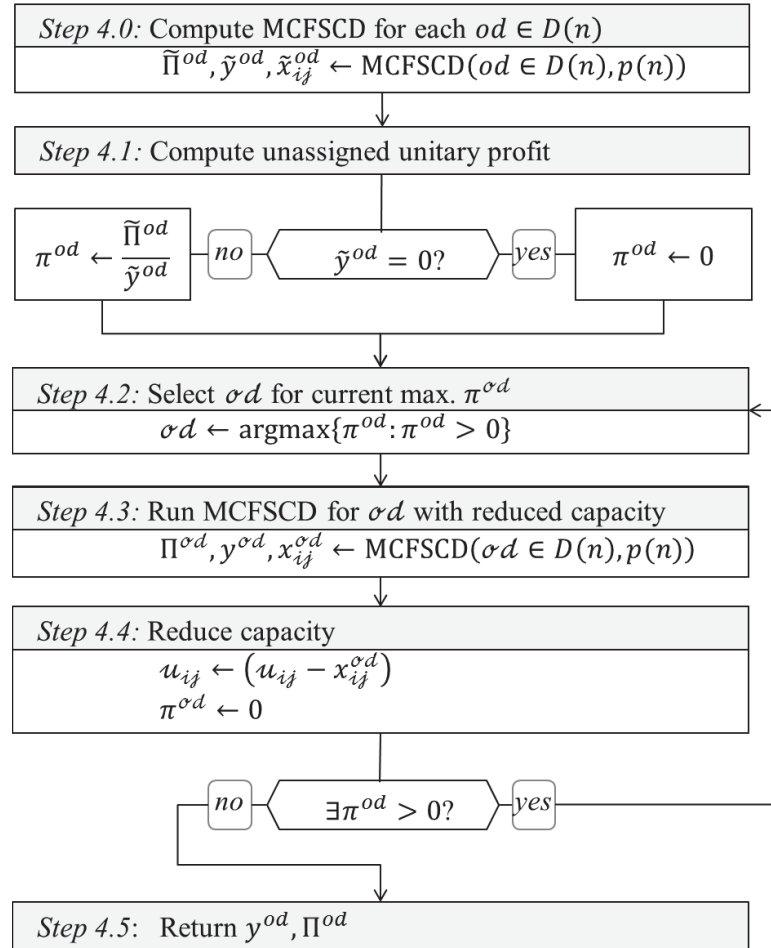


Figure 7.3 BM◦LS: assign demand algorithm (*Step 4*).

7.5.2 Minimum Cost Flow problem with Stochastic Capacities and Demand realizations (MCFSCD)

This subsection proposes a special formulation of the Minimum-Cost Flow (MCF) problem that can be used to add lanes into bundles in the LTL network while accounting for auctioned demand and capacity uncertainty.

Several works have studied stochastic MCF problems (e.g., Boyles and Waller, 2010, Ding, 2013, Ghatee and Mashemi, 2008, 2009a, 2009b, Liu and Kao, 2004) applying methods that include convex network optimization, chance constraints, fuzzy numbers, among others. Although these are very relevant works, they are not able to optimize under uncertainty related to demand and capacities. Interestingly, many of them transform the computationally complex stochastic program into a MCF type of formulation that can be solved efficiently. Optimization under uncertain demand has been proposed to solve stochastic vehicle routing and fleet management problems (Sarimveis et al. 2008, Shi et al. 2014, Simão et al. 2009 Topaloglu and Powell, 2006).

Following ideas in these works, this research formulates and proposes a solution approach for the MCFSCD that is able to optimize flows under uncertainty. The required notation is introduced below. The MCFSCD problem is solved for a specific lane $od \in D(n)$. So, this index is removed from the corresponding variables/parameters to simplify notation.

Sets

$A^{od} = A$ set of arcs included in the *load plan* between the origin and destination of lane $od \in D(n)$.

Variables

$x_{ij}^{od} = x_{ij}$ (weight/time) first stage variable that determines the desirable amount of flow in arc $(i, j) \in A$ related to the flow in lane $od \in D(n)$ for the scenario $\omega \in \Omega$.

$y^{od}(\omega) = y(\omega)$ (weight/time) second stage variable that determines the unknown amount of flow for pricing in lane $od \in D(n)$ for the scenario $\omega \in \Omega$.

$\chi_{ij}^{od}(\omega) = \chi_{ij}(\omega)$ (weight/time) second stage variable that determines the outsourced flow (additional to the unknown available capacity) in arc $(i, j) \in A$ related to the flow in lane $od \in D(n)$ for the scenario $\omega \in \Omega$.

$\Pi^{od}(\omega) = \Pi(\omega)$ (\$) maximum profit expected by selecting the desirable amount of flow x_{ij} from the flow in lane $od \in D(n)$ for the scenario $\omega \in \Omega$.

Parameters

$p(n) = p$ (\$/weigh) fixed unitary price per weight charged to the flow in lane $od \in D(n)$.

$q^{od}(\omega) = q(\omega)$ (weight/time) lane $od \in D(n)$ flow for realization $\omega \in \Omega$ (Subsection 7.3.3).

$\wp^{od}(\omega) = \wp(\omega)$ realization probability for lane flow $q(\omega)$ in scenario $\omega \in \Omega$. (Subsection 7.3.3).

$\wp_{ij}(\omega)$ probability of having unused capacity $u_{ij}(\omega)$ available in arc $(i, j) \in A$ for realization $\omega \in \Omega$. (Subsection 7.3.3).

The problem is defined as follow: For a given lane $od \in D(n)$ related to a postulated price p , the problem is determining the desirable amount of flow x_{ij} that maximizes the corresponding expected profits. The first-stage variable x_{ij} has to be selected before the

realization of unknown second-stage variables $y(\omega)$, and $\chi_{ij}(\omega)$, which are subject to constraints determined by scenario $\omega \in \Omega$. Thus,

The MCFSCD is formulated by the stochastic program (7.17)-(7.25). The carrier can only price the demand that realizes $y(\omega)$, however it has to consider a desired flow x_{ij} in advance associated to costs in its network and outsourcing costs when capacity is not sufficient. The Objective Function (7.17) captures this by computing the maximum profit $\Pi(\omega)$ as the revenues obtained charging the price p to the pricing lane flow $y(\omega)$ in scenario $\omega \in \Omega$ minus the corresponding total operational cost. Two terms comprise this cost (bigger parenthesis): (i) the total cost of serving the desired flow x_{ij} , and (ii) the cost of considering flow higher than arc capacities. Notice that (ii) corrects cost estimation when x_{ij} is higher than capacity. The Objective Function (7.17) is subject to the set of Random Constraints (7.18)-(7.25).

$$\max \Pi(\omega) = \mathbb{E}_\omega[py(\omega)] - \left(\sum_{(i,j) \in A} c_{ij}x_{ij} + \mathbb{E}_\omega \left[\sum_{(i,j) \in A} (\varsigma_{ij} - c_{ij})\chi_{ij}(\omega) \right] \right) \quad (7.17)$$

$$\begin{aligned} y(\omega) &\leq q(\omega) \\ \forall \omega \in \Omega \end{aligned} \quad (7.18)$$

$$\begin{aligned} y(\omega) &= \sum_{j \in N} x_{oj} \\ o \in N, \forall \omega \in \Omega \end{aligned} \quad (7.19)$$

$$\begin{aligned} \sum_{j \in N} x_{jd} &= y(\omega) \\ \forall i \in N, \forall \omega \in \Omega \end{aligned} \quad (7.20)$$

$$\begin{aligned} \sum_{j \in N} x_{ji} &= \sum_{j \in N} x_{ij} \\ \forall i \neq o, d \in N, \forall \omega \in \Omega \end{aligned} \quad (7.21)$$

$$\begin{aligned} x_{ij} - \chi_{ij}(\omega) &\leq u_{ij}(\omega) \\ \forall (i, j) \in A, \forall \omega \in \Omega \end{aligned} \quad (7.22)$$

$$\begin{aligned} 0 &\leq y(\omega) \\ \forall (i, j) \in A, \forall \omega \in \Omega \end{aligned} \quad (7.23)$$

$$\begin{aligned} 0 &\leq x_{ij} \\ \forall (i, j) \in A, \forall \omega \in \Omega \end{aligned} \quad (7.24)$$

$$\begin{aligned} 0 &\leq \chi_{ij}(\omega) \\ \forall (i, j) \in A, \forall \omega \in \Omega \end{aligned} \quad (7.25)$$

First, the unknown pricing flow $y(\omega)$ has to be at most equivalent to the lane demand $q(\omega)$ in scenario $\omega \in \Omega$ (Constraint (7.18)). Constraints (7.19)-(7.21) indicate flow conservation that follows the *load plan* as defined by r_{ij} , i.e. the pricing flow enters the network at the origin node for the considered lane $o \in N$ (Constraint (7.19)), exits it from the destination node $d \in N$ (Constraint (7.20)), and there is equivalency between inbound and outbound flows at intermediate nodes (Constraint (7.21)). Furthermore, Constraint (7.22) establishes that the flow carried within the carrier's network $x_{ij} - \chi_{ij}(\omega)$ (not outsourced) has to be at most equivalent to the capacity $u_{ij}(\omega)$ in scenario $\omega \in \Omega$. Recall that arcs in this problem are only those in the corresponding *load plan*. Finally, Constraints (7.23)-(7.25) are non-negativity constraints.

Again, the solution space for the stochastic program (7.17)-(7.25) is infeasible for scenarios different than the actual realizations of demand. Hence, a deterministic equivalent (DE) problem is proposed to solve it. This is achieved using a series of network transformations, a concept commonly used to solve stochastic routing problems, e.g., Topaloglu and Powell (2006). The DE uses soft constraints and appropriate penalties in the objective function to handle violations and compute the desired flow x_{ij} that

account for stochastic demand. The following sections describe the transformations require to construct the DE.

7.5.3 Network transformations

This subsection describes a series of network modifications proposed to derive an efficient DE problem for the MCFSCD. Concepts related to demand realization probabilities are introduced first. Without loss of generality assume that the set $\Omega = \{1, \dots, \omega, \dots, |\Omega|\}$ is sorted such that $q(1) < \dots < q(\omega) < \dots < q(|\Omega|)$, which implies that $y(1) < \dots < y(\omega) < \dots < y(|\Omega|)$. Let $q(0) = q(\Delta_0) = 0$, and $q(\Delta_\omega) = q(\omega) - q(\omega - 1)$ be the differential of realized demand $q(\omega)$ and $q(\omega - 1)$. Likewise, assume that $y(\omega)$ is split in intervals $y(\Delta_\omega)$ such that Constraint (7.26) holds. Thus, any realization of flow for pricing can be represented as a function of its previous realizations (Equation (7.27)). Following this idea, Equation (7.28) describes the probability $\mathcal{P}(\Delta_\omega)$ for the realization of $y(\Delta_\omega)$. Notice that probabilities decrease as scenarios increase, i.e., $\mathcal{P}(\Delta_1) = 1 > \mathcal{P}(\Delta_2) > \dots > \mathcal{P}(\Delta_{|\Omega|-1}) > \mathcal{P}(\Delta_{|\Omega|})$. Finally, the expected total income (first term in Objective Function (7.17)) can be computed using its DE as shown in Equation (7.29).

$$q(\Delta_{\omega-1}) \leq y(\Delta_\omega) \leq q(\Delta_\omega) \quad \forall \omega \in \Omega \quad (7.26)$$

$$y(\omega) = \sum_{\substack{s \leq \omega \in \Omega \\ \forall \omega \in \Omega}} y(\Delta_s) \quad (7.27)$$

$$\mathcal{P}(\Delta_\omega) = \sum_{s \in \Omega: \omega \leq s} p(s) \quad (7.28)$$

$$\mathbb{E}_\omega[py(\omega)] = p \sum_{s \in \Omega} y(\Delta_s) \mathcal{P}(\Delta_s) \quad (7.29)$$

Similarly, assume $\Omega = \{1, \dots, \omega, \dots, |\Omega|\}$ is such that $u_{ij}(1) < \dots < u_{ij}(\omega) < \dots < u_{ij}(|\Omega|)$. Let $u_{ij}(0) = u_{ij}(\Delta_0) = 0$, and $u_{ij}(\Delta_\omega) = u_{ij}(\omega) - u_{ij}(\omega - 1)$ be the differential of available capacity between $u_{ij}(\omega)$ and $u_{ij}(\omega - 1)$. The desired flow x_{ij} can be split in intervals $x_{ij}(\Delta_\omega)$ where Constraints (7.30)-(7.31) hold. Following this idea, Equation (7.32) indicates the probability $\mathcal{P}_{ij}(\Delta_\omega)$ of serving the segment of desired demand $x_{ij}(\Delta_\omega)$ by capacity available in the LTL network. Again, notice that probabilities decrease as scenarios increase, i.e., $\mathcal{P}_{ij}(\Delta_1) = 1 > \mathcal{P}_{ij}(\Delta_2) > \dots > \mathcal{P}_{ij}(\Delta_{|\Omega|-1}) > \mathcal{P}_{ij}(\Delta_{|\Omega|})$. Finally, the expected total cost (second term in Objective Function (7.17)) can be computed using its DE as shown in Equation (7.33).

$$u_{ij}(\Delta_{\omega-1}) \leq x_{ij}(\Delta_\omega) \leq u_{ij}(\Delta_\omega) \quad (7.30)$$

$$\forall \omega \in \Omega, \forall (i, j) \in A$$

$$x_{ij} = \sum_{\substack{s \in \Omega \\ \forall (i, j) \in A}} x_{ij}(\Delta_\omega) \quad (7.31)$$

$$\mathcal{P}_{ij}(\Delta_\omega) = \sum_{s \in \Omega: \omega \leq s} \mathcal{P}_{ij}(s) \quad (7.32)$$

$$\sum_{(i,j) \in A} c_{ij} x_{ij} + \mathbb{E}_\omega \left[\sum_{(i,j) \in A} (\zeta_{ij} - c_{ij}) x_{ij}(\omega) \right] = \sum_{(i,j) \in A} \sum_{s \in \Omega} x_{ij}(\Delta_\omega) (\mathcal{P}(\Delta_s) c_{ij} + (1 - \mathcal{P}(\Delta_s)) \zeta_{ij}) \quad (7.33)$$

A series of network transformations are required to convert The MCFSCD (7.17)-(7.25) into its DE. These transformations are illustrated in Figure 7.4, where each arc in the *load plan* for lane $od \in D(n)$ (Figure 7.4(a)) is transformed (Figure 7.4(b)) to generate its new representation using the new sets of nodes and arcs: $N(\Omega)$ and $A(\Omega)$ respectively (Figure 7.4(c)).

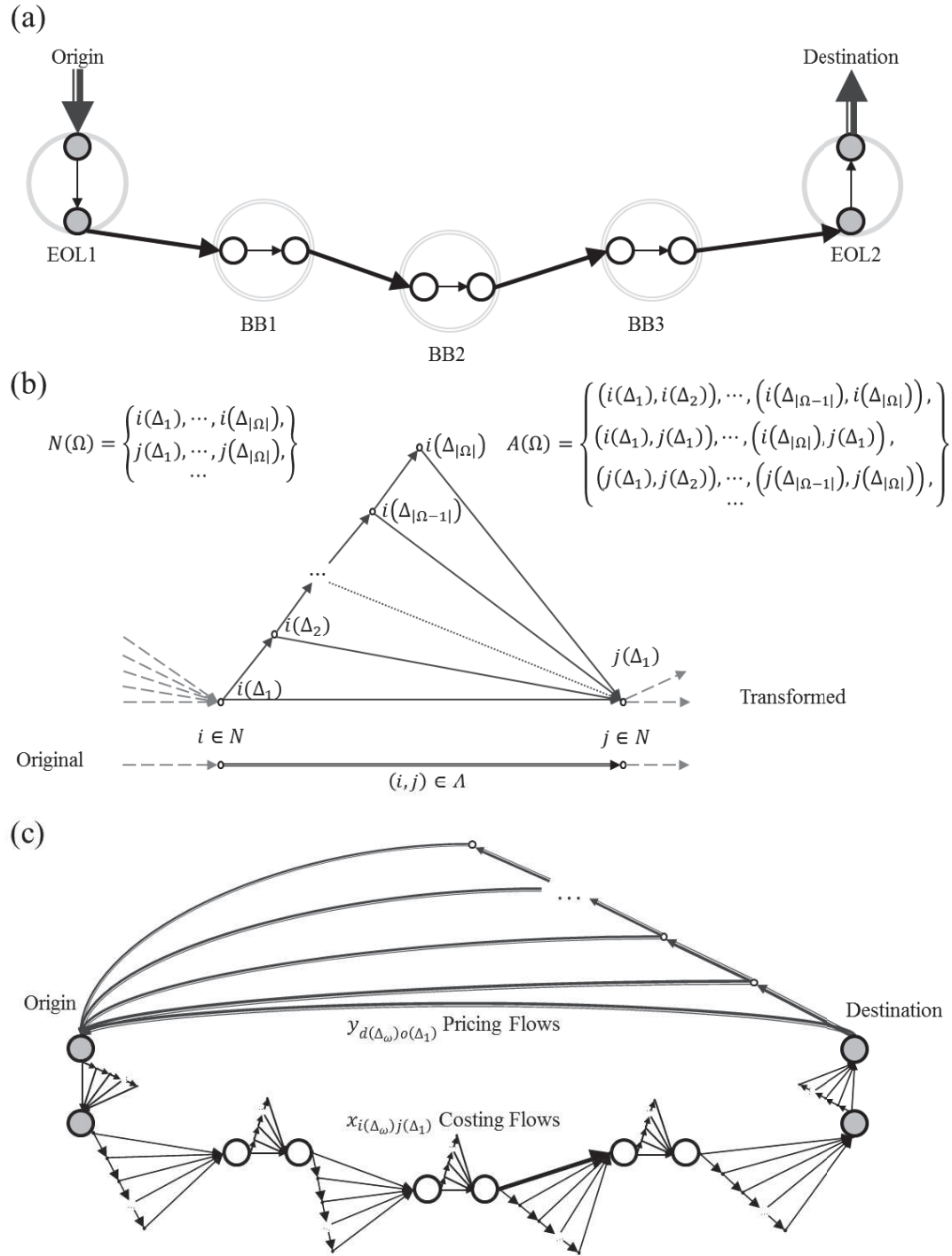


Figure 7.4 Network transformations: (a) *load plan*, (b) *arc transformation*, and (c) *transformed load plan*.

Formally, each node $i \in N$ is replaced by a set of $|\Omega|$ nodes representing each differential Δ_ω , i.e., $N(\Omega) = \{i(\Delta_\omega), \forall \omega \in \Omega, \forall i \in N\}$. Additionally, each arc $(i, j) \in A \cup \{(d, o)\}$ is replaced by a group of arcs $A(\Omega)$. The arc (d, o) is an artificial arc whose tail and head are the $od \in D(n)$ lane destination d and origin o respectively. Let $A(\Omega, od) \subset A(\Omega)$ be the subset of modified arcs associated to this artificial arc. This requires to find the right balance between supply and demand in the problem. Likewise, $A(\Omega) = A_1(\Omega) \cup A_2(\Omega)$, where the first subset $A_1(\Omega) = \{(i(\Delta_{\omega-1}), i(\Delta_\omega)) : \forall i(\Delta_\omega), i(\Delta_{\omega-1}) \in N(\Omega), \omega \in \Omega \setminus \{1\}\}$ accounts for arcs between subsequent differential realizations $i(\Delta_{\omega-1})$ and $i(\Delta_\omega)$, and the second subset $A_2(\Omega) = \{(i(\Delta_\omega), j(\Delta_1)) : \forall i(\Delta_\omega), j(\Delta_1) \in N(\Omega) : (i, j) \in A\}$ connects each differential realization $i(\Delta_\omega)$ to the first realization of the next node $j(\Delta_1)$.

Now, the DE of the MCFSCD can be formally defined.

7.5.4 Deterministic equivalent (DE) problem

The DE is formulated as the MCF problem (7.37)-(7.40). The corresponding variables and sets are summarized below. Other parameters were previously defined.

Sets and indexes

$N(\Omega)$ set of transformed nodes required to derive the DE of the MCFSD.

$A(\Omega)$ set of transformed arcs required to derive the DE of the MCFSD.

$A_1(\Omega)$ set of arcs used for flow conservation in the transformed network

$A_2(\Omega)$ set of arcs used pricing/costing in the transformed network

$A(\Omega, od)$ subset of arcs associated to the artificial arc (d, o)

o index used to identify the node in N associated to the origin of lane $od \in D(n)$

d index used to identify the node in N associated to the destination of lane $od \in D(n)$

Variables

y_{ij} (weight/time) recourse actions related to the pricing flow traversing arc $(i, j) \in A(\Omega, od)$.

x_{ij} (weight/time) recourse actions related to the costing flow traversing arc $(i, j) \in A(\Omega) \setminus A(\Omega, od)$.

Π (\$) maximum expected profit

Parameters

p_{ij} (\$/weight) expected marginal income for a unit of flow priced in arc $(i, j) \in A(\Omega)$. Equation (7.34) sets this expected value combining the right arcs in the transformed network with the derivation obtained from Equation (7.29). Thus, only the flow traversing modified arcs associated to the artificial arc (d, o) contributes to the expected income.

$$p_{ij} = \begin{cases} p * \mathcal{P}(\Delta_\omega) & \text{if } (i, j) \in A(\Omega, od) \cap A_2(\Omega) \\ 0 & \text{otherwise} \end{cases} \quad (7.34)$$

c_{ij} (\$/weight) expected marginal cost for a unit of flow traversing arc $(i, j) = (i(\omega), j(s)) \in A(\Omega)$. Equation (7.35) sets this expected value combining the corresponding arcs in the transformed network with the derivation obtained from Equation (7.33). Thus, only the flow traversing modified arcs associated to those in the LTL network contribute to the expected cost.

$$c_{ij} = \begin{cases} (\mathcal{P}(\Delta_\omega)c_{ij} + (1 - \mathcal{P}(\Delta_\omega))\varsigma_{ij}) & \text{if } (i, j) \in A_2(\Omega) \setminus A(\Omega, od) \\ 0 & \text{otherwise} \end{cases} \quad (7.35)$$

u_{ij} (weight/time) capacity for arc $(i, j) \in A(\Omega)$ in the modified network. Equation (7.36) sets arc capacity according to the derivations in Constraints (7.26) and (7.30) for pricing and costing arcs in subset $A_2(\Omega)$, and allowing a logical flow propagation for the related flow-conservation arcs in subset $A_1(\Omega)$.

$$u_{ij} = \begin{cases} q(\Delta_\omega) & \text{if } (i, j) \in A_2(\Omega) \cap A(\Omega, od) \\ u_{ij}(\Delta_\omega) & \text{if } (i, j) \in A_2(\Omega) \setminus A(\Omega, od) \\ q_{ij}(|\Omega|) - u_{ij}(\omega) & \text{if } (i, j) \in A_1(\Omega) \cap A(\Omega, od) \\ u_{ij}(|\Omega|) - u_{ij}(\omega) & \text{if } (i, j) \in A_1(\Omega) \setminus A(\Omega, od) \end{cases} \quad (7.36)$$

The Objective Function (7.37) maximizes the total expected profit Π for the desired assignment of flow in lane $od \in D$ into the LTL network, where the first term computes the total expected income (using the artificial arc (d, o) to represent and price the corresponding desired flow), and the second term computes the total expected cost.

$$\max \Pi = \sum_{(i,j) \in A(\Omega)} p_{ij} y_{ij} - c_{ij} x_{ij} \quad (7.37)$$

$$\sum_{\forall (j,i) \in A(\Omega, od)} y_{ji} + \sum_{\substack{\forall (j,i) \in A(\Omega) \setminus A(\Omega, od) \\ i = N(\Omega)}} x_{ji} = \sum_{\forall (i,j) \in A(\Omega, od)} y_{ij} + \sum_{\forall (i,j) \in A(\Omega) \setminus A(\Omega, od)} x_{ij} \quad (7.38)$$

$$\begin{aligned} 0 &\leq y_{ij} \leq u_{ij} \\ \forall (i, j) &\in A(\Omega, od) \end{aligned} \quad (7.39)$$

$$\begin{aligned} 0 &\leq x_{ij} \leq u_{ij} \\ \forall (i, j) &\in A(\Omega) \setminus A(\Omega, od) \end{aligned} \quad (7.40)$$

Constraint (7.38) appropriately combines sets and variables previously defined to guarantee flow conservation throughout the modified network. Constraints (7.39) and (7.40) are non-negativity constraints. The directed loop enforced by this network

modification implies that the minimum expected total profit is $\Pi = 0$ occurring either when no-flow is assigned to the network, or when the best flow corresponds to the break-even point for this price and operational configuration.

As usual in stochastic programming, the DE of the MCFSCD suffers from the curse of dimensionality. However, the specific structure of the DE (7.37)-(7.40) makes possible to frame it as a deterministic MCF problem (Ahuja et al. 1995). Interestingly, there are several algorithms that solve the MCF problem in polynomial time. Király and Kovács (2012) summarize many of them (Table 4.3 in Chapter 4), which is beneficial for its solution.

After solving the DE of the MCFSCD using one of these algorithms, the corresponding outputs are:

Outputs

$\Pi^{od} \leftarrow \Pi$ (\$) maximum expected profit for the analyzed lane, which will be used to compute unitary profit (*Step 4.1*) added to the profit from other lanes to build bids.

$x_{ij}^{od} \leftarrow x_{ij}$ (weight/time) costing flow in the modified network, which will be used to reduce capacities before assigning other lanes

$y^{od} \leftarrow \sum_{(i,j) \in A_2(\Omega)} y_{ij}$ (weight/time) amount of flow desirable from the lane $od \in D(n)$, which is information required to if the lane used to construct a bid.

7.5.5 Build bundles

This section describes a procedure to build bundles by combining lanes with positive desired flow whose *load plans* overlap in the LTL network (Figure 7.5). Specific notation is described below.

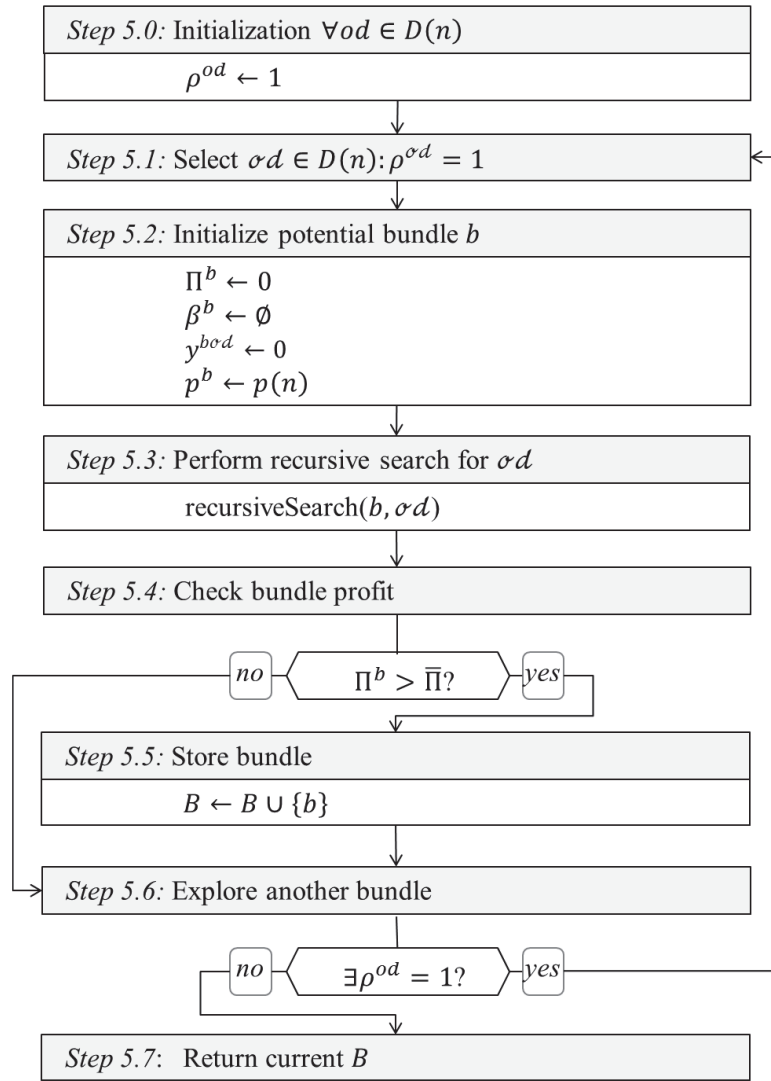


Figure 7.5 BMoLS: build bundles algorithm (Step 5).

Variables

$\rho^{\sigma d}$ binary variable that indicate whether lane $\sigma d \in D(n)$ has been explored in the recursive search ($\rho^{\sigma d} = 1$) or not ($\rho^{\sigma d} = 0$).

Parameters

$\phi_{od}^{\sigma d}$ binary parameter that indicate whether lanes $od, \sigma d \in D(n)$ share one or more arcs in their corresponding *load plans* $\phi_{od}^{\sigma d} = 1$ or not $\phi_{od}^{\sigma d} = 0$.

$\bar{\Pi}$ (\$) minimum expected profit accepted for any bid submitted to the auction (Section 7.4).

A bundle b is constructed by bundling all lanes $\sigma d \in D(n)$ with positive and overlapping flows in the LTL network. Overlaps are determined by the arcs shared in the corresponding *load plans*. Thus, the expected profit Π^b for a potential bid b is computed as the sum of expected profits $\Pi^{\sigma d}$ for each of these lanes. Only bundles with acceptable expected profits are stored as definite bids, i.e., $\Pi^b \geq \bar{\Pi}$.

The bundling process, that recursively searches for lanes with overlapping paths and positive flows, is illustrated in Figure 7.5, where a. *Step 5.0* initializes the process indicating that no lane has been explored yet, i.e., $\rho^{\sigma d} = 1, \forall \sigma d \in D(n)$. The recursive search starts from any lane $\sigma d \in D(n)$ that has not been explored, i.e., $\rho^{\sigma d} = 1$ (*Step 5.1*). Then, a potential bundle b is initialized (*Step 5.2*) and a recursive search is conducted from σd searching other overlapping nodes and updating the specific features of b when required (*Step 5.3*). Specific details about this search are provided in Subsection 7.5.6. When the search stops, the updated bundle profit Π^b is compared with respect to the acceptable one $\bar{\Pi}$. If the former is greater than or equal to the latter, a bid related to this bundle b is added to the set of bids B (*Step 5.5*). If there are unexplored lanes after the search conducted for the latest bundle (*Step 5.6*), the process returns to *Step 5.1*. Otherwise, the process ends and the current updated set of bids B is returned.

The following subsection provides additional details for the recursive search conducted in Step 5.3.

7.5.6 Recursive search

The recursive search conducted in *Step 5.3* starts from a specific lane $\sigma d \in D(n)$ and continues to all other overlapping lanes $od \in D(n)$. When a specific overlapping lane is selected the process repeats assuming it as the current one. This is a depth first search conducted over a network where a connection exists whenever two lanes overlap.

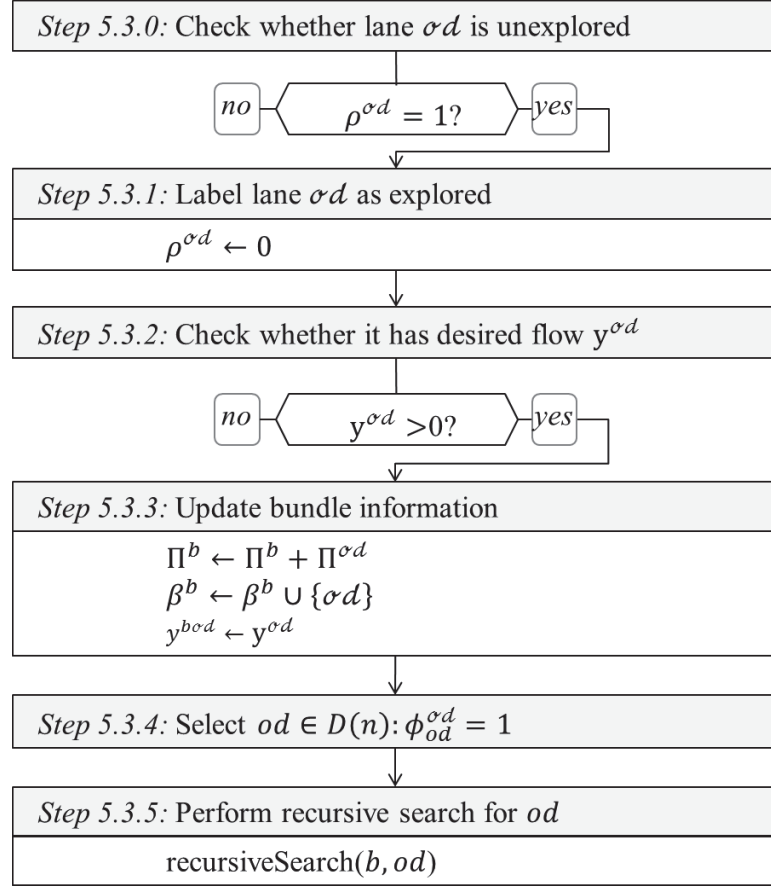


Figure 7.6 BM•LS: recursive search algorithm (Step 5.3).

Figure 7.6 illustrates this search. As observed in Section 7.5.5, the inputs for this process are an potential bundle b and a lane σd . *Step 5.3.0* checks whether σd has been explored in the search, i.e., $\rho^{\sigma d} = 1$. If this is the case, *Step 5.3.1* labels the lane as explored, i.e., $\rho^{\sigma d} = 0$, and checks whether this lane is related to a positive desired flow

$y^{od} > 0$, which was obtained from the “assign demand” *Step 4* (Subsection 7.5.5). If this is the case, *Step 5.3.3* updates the information for the current bundle, i.e., $\Pi^b, \beta^b, y^{b \circ d}$. Then, for all lanes $od \in D(n)$ that overlap with σd , i.e., $\phi_{od}^{\sigma d} = 1$ (*Step 5.3.4*), the recursive search is conducted (*Step 5.3.5*). Notice that when one of the conditions in *Steps 5.3.0* or *5.3.2* does not hold, the recursive search returns to the *Step 5.3.5* associated to the previous lane and a new overlapping lane is fathomed.

7.5.7 Select lane to remove

Lanes related to low unitary profits are removed to allow other lanes to be included in a new bid. This process is guided by the “select lane to remove” algorithm (Figure 7.7). The algorithm starts assuming that there are no lanes to remove (*Step 6.0*). Then, the unitary profit π^{od} is computed for each lane (*Step 6.1*). First, lanes od not related to the current price $p^{od} \neq p(n)$ are analyzed and the one with lowest $\pi^{od} > 0$ is selected. If there are no lanes with this characteristic, either because they were already removed or they are not considered in the desired flows, lanes related to the current price $p^{od} = p(n)$ are analyzed and the one with lowest $\pi^{od} > 0$ is selected. If a new lane od to remove is found, then it is returned, i.e., $\sigma d \leftarrow od$. Otherwise, an empty index is returned, i.e., $\sigma d \leftarrow \emptyset$, which stops the iterations of the *inner loop*.

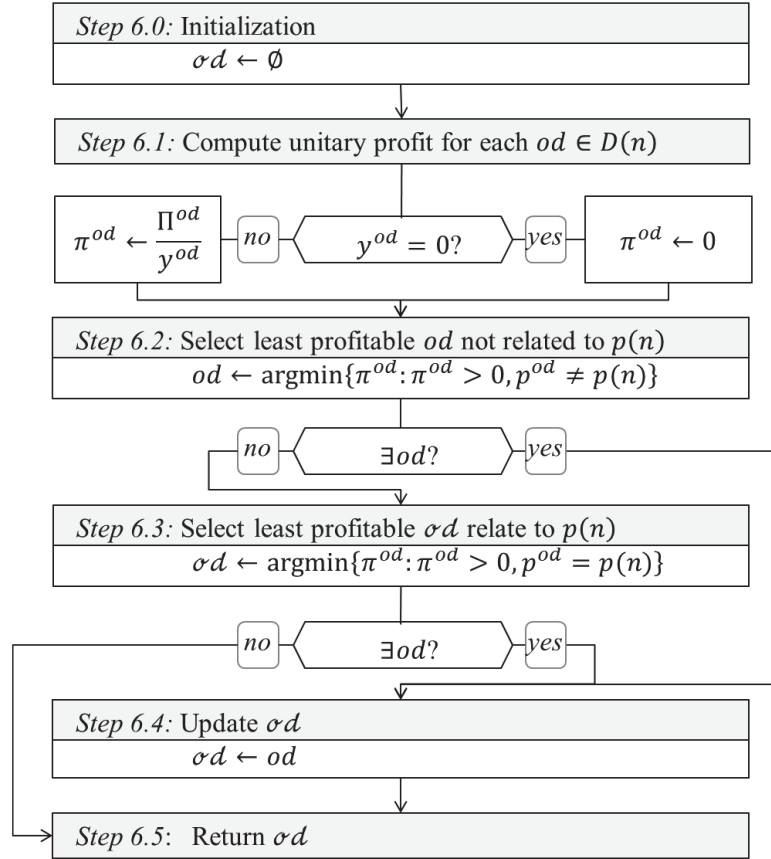


Figure 7.7 BM◦LS: Select lane to remove algorithm (Step 6).

The application of BM◦LS is illustrated with a numerical example in the next section.

7.6 Numerical results

This section presents a numerical example illustrating the use of BM◦LS, which is coded in C++. Király and Kovács (2012) test the computational efficiency of different MCF software packages and algorithms. They find the C++ Library for Efficient Modeling and Optimization in Networks (LEMON) (Dezső et al. 2011) and its Network Simplex to be one of the most competent algorithms to solve the MCF problem in large scale networks. Therefore, these modules are integrated to solve the DE MCF associated to the MCFSCD solved by BM◦LS. LEMON is developed by the Computational

Infrastructure for Operations Research (COIN-OR) and also used for network manipulation. Other modules are developed by the authors. Experiments are run in a desktop with the following characteristics: Processor Intel® Core™2 Duo CPU E8400 @ 3.00GHz, Installed memory (RAM) 4.00GB.

The numerical experiment is defined as follows. Consider an LTL carrier with a network composed by two EOLs (EOL1 and EOL2) and two BBs (BB1 and BB2). The carrier sends a straight truck daily in both directions between each EOL-BB pair. The capacity of each truck is 14,000 *lb* equivalent to 98,000 *lb/week*. Likewise, it sends a tandem of 2 pup trailers every three days in both directions between BBs. The capacity is 44,000 *lb* (22,000 *lb* for each pup) equivalent to 103,000 *lb/week*. Between each pair of terminals (first two columns), Table 7.1 summarizes the operational characteristics related to service time interval, cost in the LTL network, and outsourcing cost (columns 3 to 5). Likewise, the carrier has estimated a set Ω with three scenarios of capacity realizations: low $\omega = 1$, medium, $\omega = 2$, and high $\omega = 3$. The corresponding realization probabilities and realization values are presented in columns 6 to 11.

Table 7.1 Operational characteristics for movements between terminals

i	j	Interval (days)	c_{ij} (\$/k lb)	ζ_{ij} (\$/k lb)	$u_{ij}(1)$ (k lb/week)	$p_{ij}(1)$ (%)	$u_{ij}(2)$ (k lb/week)	$p_{ij}(2)$ (%)	$u_{ij}(3)$ (k lb/week)	$p_{ij}(3)$ (%)
EOL1	BB1	1	10	20	17	10	41	60	66	30
BB1	EOL1	1	10	20	32	70	40	25	45	5
BB1	BB2	3	40	70	22	10	46	60	71	30
BB2	BB1	3	40	70	37	70	45	25	50	5
BB2	EOL2	1	10	20	17	10	41	60	66	30
EOL2	BB2	1	10	20	32	70	40	25	45	5

Similarly, for each terminal (column 1), Table 7.2 summarizes the operational characteristics related to service cost in the LTL network (column 2), and outsourcing

cost (columns 3), and corresponding realization probabilities and realization values for capacities in each scenario (columns 4 to 9).

Table 7.2 Operational characteristics for movements within terminals

i	c_i (\$/k lb)	ζ_i (\$/k lb)	$u_i(1)$ (k lb/week)	$p_i(1)$ (%)	$u_i(2)$ (k lb/week)	$p_i(2)$ (%)	$u_i(3)$ (k lb/week)	$p_i(3)$ (%)
EOL1	8	16	50	10	74	60	99	30
EOL2	8	16	60	10	84	60	109	30
BB1	2	10	190	10	214	60	239	30
BB2	2	10	170	10	194	60	219	30

This carrier is participating of an LTL CA. After a preliminary analysis of the lanes communicated by the shipper, it decides to prepare bids for the lanes summarized in Table 7.3, where column 1 indicates the EOL related to the lane origin, column 2 the EOL related to the destination, column 3 the reservation price, and columns 4-9 the corresponding realization probabilities and values for demand in each lane.

Table 7.3 Lanes in the LTL CA considered for bid preparation

o	d	Load Plan	p^{od} (\$/ k lb)	$q^{od}(1)$ (k lb/week)	$p^{od}(1)$ (%)	$q^{od}(2)$ (k lb/week)	$p^{od}(2)$ (%)	$q^{od}(3)$ (k lb/week)	$p^{od}(3)$ (%)
EOL1	EOL2	EOL1-BB1-BB2-EOL2	110	25	70	50	20	100	10
EOL2	EOL1	EOL2- BB2-BB1-EOL1	90	10	20	13	40	18	40

The combination of these 4 terminals and 2 lanes results in a modified network with 32 nodes and 60 arcs, which reflects the acknowledged curse of dimensionality. However, it takes less than 1 second to return the set of bids, which is summarized in Table 7.4.

Table 7.4 Set of bids

b	β^b	y^b	p^b	Π^b
0	(EOL1,EOL2)	25	110	725
1	(EOL1,EOL2)	25	90	325
	(EOL2,EOL1)	10	90	
2	(EOL2,EOL1)	10	90	100

This example demonstrates the influence that stochastic realizations of demand and capacity have over the bid construction problem. In this case, BM \circ LS selects the realizations of demand for the low scenario ($\omega = 1$) in each lane. This gives the highest expected marginal income for a unit of priced flow. Since terminals have sufficient capacity, the desired demand can be handled for the scenario with lowest capacity. More interestingly, BM \circ LS assigns more load (25 k lb/week) to the transportation arc EOL1-BB1 than the one that is certain for this arc, i.e., 17 k lb/week with 100% realization probability. So, it says that it is worth to assign such higher load because the next differential of capacity has a large realization probability, i.e., 41 k lb/week = [17 (with 100%) + 24 (with 90%)] k lb/week. Similar results occur with the segments BB1-BB2 and BB2-EOL2. However, this is not the case for operations in the other direction, where assuming a realization of capacity for the medium differential of demand is highly risky, e.g., between EOL2 and BB2 in the low-capacity differential scenario there is a 100% probability of having 32 k lb/week available but in the medium capacity differential there is a lot of uncertainty for the availability of 40 k lb/week = [32 (with 100%) + 8 (with 30%)].

This shows the importance of considering stochastic demand and capacity when planning LTL operations like those required for bidding in LTL CA.

The next subsection summarizes this work and provides future research directions.

7.7 Conclusions

In the context of LTL CA, this research studies the bidding problem faced by LTL carriers. BM \circ LS, an efficient algorithmic framework to construct bundles that account for demand and capacity uncertainty, is proposed for this purpose.

The main contributions of this work are: (1) formulating the context of LTL CA, and (2) proposing the first LTL bidding model in literature. Additionally, this model addresses the following limitations of incumbent TL bidding advisory models: (i) using a value-based pricing approach to build bundles that maximize the expected profits of the bids and properly handle prices following the rules of CAs, (ii) using demand segmentation to determine the maximum LTL flow that the carrier is willing to serve within each bundle, and (iii) incorporating demand and capacity uncertainty in the construction of bundles.

BM \circ LS finds bundles at a tractable computational time, which is important and meaningful for trucking analysts that require evaluating networks with hundreds of lanes in a LTL CA. Computational burden is reduced by a novel DE formulation of the MCFPSCD requires to be solved several times in the framework. This is possible through network transformations that convert the two-stage stochastic problem into its deterministic equivalent and find aggregated flows optimized for uncertainty.

A numerical example illustrates the application of BM \circ LS and shows its ability to account for stochastic demand and capacity under different realization scenarios.

CHAPTER 8. CONCLUSION

8.1 Summary, findings, and contributions

This dissertation studies the problem faced by carriers that require to bundle and price trucking services as part of the negotiation process with shippers. This is a challenging task driven by three distinctive elements: (i) shipper preferences, (ii) carrier operation, i.e., truckload (TL) and less-than-truckload (LTL), and (iii) lane flow uncertainty. The main motivations of this dissertation are presented below.

This study is motivated by the real world implementation of combinatorial auctions (CA) in trucking markets, which have provided significant savings for both shippers and carriers. Likewise, bundling improves inefficiencies in asset utilization, e.g., reduced empty trips and unused capacity, which in turn contributes to reduce freight-related externalities, e.g., emissions, congestion, safety, infrastructure deterioration, etc. Furthermore, new paradigms are proposed to improve modeling gaps found in previous literature. The important findings obtained from this research are presented next.

8.2 Findings

Bundling and pricing trucking services is a very interesting problem that deserves more attention from the research community. Improvements in this direction can significantly benefit shippers, carriers, and society. However, this is not an easy task because the pricing/bundling problem involves addressing hard transportation and

combinatorial problems. Therefore, creative approaches with the right balance between accuracy and efficiency are required.

Additionally, modeling this complex interaction requires a good detailed understanding of the relationship between shippers and carriers, negotiation interfaces, behavior, and operation. Although it is easy to postulate a theoretical problem that is complex and interesting from the academic perspective, it does not mean that such problem is relevant in practice. This research narrows the gap between theory and practice by paying special attention to these details and developing tools that provide good quality solution given the demanding complexity of the problem.

Although understanding behavior is crucial to study the interaction of agents in transportation systems, researchers tend to underestimate its importance. Thus, "economic rationality" is commonly assumed in models where agents always take the most economic decisions, e.g., the cheapest options. Although paradigms for passenger transportation have gradually relaxed this assumption, i.e., considering bounded rationality, it is erroneously believed that firms involved in freight interactions are exclusively driven by monetary incentives. This research finds that although prices/costs are very important to determinant the attractiveness and selection of trucking services, there are other behavioral attributes influencing this decision. This work presents a rigorous econometric exercise that supports this behavior, which was timidly reported in previous research but never corroborated statistically.

Similarly, literature is plenty of models that assume complete and perfect information for operational decisions. However, transportation agents operate in an environment surrounded by uncertainty, which is commonly relaxed in transportation models. This

work recognizes the importance of stochastic effects for decision making and develops models that properly handle them. This is important to take decisions when information is ambiguous.

In addition to these general findings, several specific research contributions result from this dissertation.

8.3 Contributions

This work expands and improves the current knowledge in transportation research with higher impact in the area of freight and logistics modeling. There are a number of contributions related to each objective met in the dissertation.

Next objectives are recapped and related to the corresponding contributions obtained.

- *Objective 1.* Understand shipper preferences toward truck-service selection using econometric analysis.

This objective is met in Chapter 2. As contributions, this chapter provides a comprehensive understanding of shipper preferences, postulates a set of pragmatic attributes to explain truck-service selection, quantifies the shipper willingness to pay (WTP) for these attributes, and provides meaningful negotiation guidance for shippers and carriers based on behavioral inferences.

- *Objective 2.* Develop a framework for demand clustering in TL networks based on historical data of lane flows and prices.

This objective is met in Chapter 3, where a systematic framework for demand clustering in freight logistics networks is proposed and is a contribution to literature itself. This framework incorporates economic interdependencies among clustered lanes that reflects network effects, considers historical market prices in

the clustering process, integrates uncertainty associated to historical variations on lane prices and volume, and is computationally efficient.

- *Objective 3.* Develop a model for demand bundling in TL networks that considers value-based pricing, and demand segmentation.

Chapter 4 meets the objective and contributes to literature developing a bundling model for TL services that handles bundle generation, value-based pricing, and flow segmentation explicitly.

- *Objective 4.* Develop a model for demand bundling in TL networks that considers value-based pricing, demand segmentation, and stochastic lane flows.

The latter contributions are expanded in Chapter 5, where the objective is met incorporating lane uncertainty into the TL bundle construction process.

- *Objective 5.* Demonstrate the economic benefits of routing strategies considering in-vehicle consolidation in the development of bundles for trucking service.

This objective is met in Chapter 6, demonstrating these benefits as research contribution.

- *Objective 6.* Develop a model for demand bundling in LTL networks that considers value-based pricing, demand segmentation, and stochastic lane flows.

Chapter 7 meets this objective. It combines available information to derive the taxonomy of LTL CA and expands the contributions from previous chapters by addressing, for the first time, the bundling/pricing problem from an LTL perspective. This model is based on value-based pricing, it properly handles valuation rules, and segments lane to define the maximum flow that the carrier is

willing to serve in each bundle. Furthermore, it incorporates demand uncertainty in the construction of bundles.

These contributions are elaborated on top of relevant and meaningful works developed by many researchers in the past. Likewise, there are several opportunities to expand and improve the work proposed in this dissertation. These extensions are summarized and presented next.

8.4 Future research directions

The following future research directions are identified and proposed as extensions and improvements of the current work.

8.4.1 Shipper preferences

The following research directions can be explored to improve the quality of the discrete choice experiment conducted in Chapter 2.

- Although there is sufficient variability and a large number of observations for hypothetical carriers, future research can significantly benefit from a larger sample. This would allow the incorporation of additional variables that potentially explain the unobserved heterogeneity associated to random parameters, e.g., shipment type, commodity transporter, economic sector of the shipper, geography,
- The amount of information delivered to the respondent might propitiate attribute-processing-strategies (APS) (e.g., Puckett and Hensher, 2008). Future developments will test whether APS exist and approaches to mitigate it, e.g., improved survey design.

8.4.2 Demand clustering

The following research directions can be explored to expand the scope of the work conducted in Chapter 3 and improve its performance.

- Accounting for modes that not only benefit from economies of scope/frequency but also scale/density by developing appropriate methods to capture the bilateral utilities between lanes.
- Exploring additional operational constraints not captured in the model (specifically in Module 2). Practically, any possibility can be explored and complexity will change as a function of the complexity of the implemented approach.
- Similarly, numerical results show that the linear program (LP) used in Module 2 roughly contributes to 46% of computational time. So improvements can considerably increase the performance of the overall algorithm, e.g. framing it as a minimum-cost flow (MCF) problem and using a MCF algorithm.
- Algorithmic efficiency can be improved by developing new efficient approaches in Module 3, which finds tours and updates interconnections. Currently, this module contributes to roughly 53% of overall computational time. The fundamental properties of efficient algorithms that explore cycles in networks can be approached with this purpose, e.g., the efficient Tarjan's algorithm (Tarjan, 1972)

8.4.3 Pricing and bundling algorithms

The following research directions can be explored to expand the scope of the algorithms proposed in Chapters 4 to 7.

- Similarly to Song and Regan (2003 and 2005), limited availability of vehicles due to fleet size and depot location is not considered in Chapter 4 and Chapter 5. Further developments can deal with this assumption. Notice that this will involve a drastic reevaluation of using the minimum-cost flow (MCF) problem as backbone of the framework and potentially losing its computational efficiencies.
- The algorithm proposed in Chapter 6 can be accelerated in future research. For example, exploring parallel computing (Bader et al. 2004; Melab et al. 2012), and complementing it with hybrid-metaheuristics, e.g., taboo search (Hung and Chen 2011).
- Similarly, the modular structure of the algorithms proposed in these chapters, give flexibility to improve efficiencies by implementing more advanced methods without compromising the overall assembly.

8.4.4 Other

Additional extensions are presented below.

- The impact of favoring larger trucks for consolidation should be analyzed from a macroscopic perspective, which will determine the (positive/negative) externalities and network effects associated with this behavior. It is expected that consolidation would reduce the number of truck-miles and, hence, reduce

emissions, traffic congestion, accidents, and pavement deterioration. However, this has to be validated with appropriate performance measures, models and data.

- The bundling/pricing strategy addressed in this research can be tested in a game theoretical framework to estimate its impact in the larger economy. An agent based simulation where several agents compete to serve one or many shippers is envisioned.

REFERENCES

- Abrache, J., Crainic, T. G., Gendreau, M., Rekik, M., 2007. Combinatorial auctions. *Annals of Operations Research*, 153(1), pp. 131-164.
- Ackermann, H., Ewe, H., Kopfer, H., Küfer, K. H. (2011). Combinatorial auctions in freight logistics. In *Computational Logistics, Lecture Notes in Computer Science* 6971, pp 1-17. Springer Berlin Heidelberg.
- Ahuja R. K., T.L. Magnanti, and J.B. Orlin. *Network Flows: Theory, Algorithms, and Applications*, Prentice-Hall, Inc. 1993.
- Andersem, J., Christiansen, M., Crainic, G. T., Grønhaug, R., 2011. Branch and price for service network design with asset management constraints. *Transportation Science*, 45(1), 33-49.
- Anderson, Christopher M., James J. Opaluch, and Thomas A. Grigalunas. "The demand for import services at US container ports." *Maritime Economics & Logistics* 11, no. 2 (2009): 156-185.
- Andraski, J. C., 2010. Managing Customer Expectations. Voluntary Interindustry Commerce Solutions (VICS). Spring 2010 Symposium. Lehigh University. <http://www.lehigh.edu/~inchain/documents/VICS.pdf>. Accessed September 29, 2014.
- Anthonisse, J. M. The rush in a directed graph. *Stichting Mathematisch Centrum. Mathematische Besliskunde*, BN 9/71, 1971, pp. 1-10.

- Anthonisse, J. M. The rush in a directed graph. Stichting Mathematisch Centrum. Mathematische Besliskunde, BN 9/71, 1971, pp. 1-10.
- Bader, D. A., Hart, W. E., Philips, C. A., 2004. Parallel algorithm design for branch and bound. In H.J. Greenberg (Eds.), *Tutorials on Emerging Methodologies and Applications in Operations Research*, Kluwer Academic Press, (Chapter 5), pp. 1-44.
- Balcombe, K., I. Fraser, and L. Harris. "Consumer willingness to pay for in-flight service and comfort levels: A choice experiment." *Journal of Air Transport Management* 15, no. 5 (2009): 221-226.
- Banerjee, A. (2009). Simultaneous determination of multiproduct batch and full truckload shipment schedules. *International Journal of Production Economics*, 118(1), 111-117.
- Banomyong, Ruth, and Nucharee Supatn. "Selecting logistics providers in Thailand: a shippers' perspective." *European Journal of Marketing* 45, no. 3 (2011): 419-437.
- Barcos, L., Rodríguez, V., Álvarez, M. J., & Robusté, F. (2010). Routing design for less-than-truckload motor carriers using ant colony optimization. *Transportation Research Part E: Logistics and Transportation Review*, 46(3), 367-383.
- Barnhart, C., Johnson, E.L., Nemhauser, G.L., Savelsbergh, M.W.P., Vance, P.H., 1998. Branch-and-price: Column generation for solving huge integer programs. *Operations Research*, 46(3), pp. 316-329.
- Barnhart, C., Kim, D. (1995). Routing models and solution procedures for regional less-than-truckload operations. *Annals of operations research*, 61(1), 67-90.
- Basu, Debasis, and John Douglas Hunt. "Valuing of attributes influencing the attractiveness of suburban train service in Mumbai city: A stated preference approach." *Transportation Research Part A: Policy and Practice* (2012).

- Baykasoglu, A., Kaplanoglu, V., 2011. A multi-agent approach to load consolidation in transportation. *Advances in Engineering Software*, 42, pp. 477–490.
- Belson, K. Keeping Trucks Full, Coming and Going. *The New York Times*, April 22, page F2, New York, 2010.
- Ben-Akiva, M., Bradley, M., Morikawa, T., Benjamin, J., Novak, T., Oppewal, H., Rao, V., 1994. Combining revealed and stated preferences data. *Marketing Letters* 5 (4), 335-349.
- Bhat, C.R., 2003. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. *Transportation Research Part B* 37 (1), 837–855.
- Bland, R. G., and D. L. Jensen. On the computational behavior of a polynomial-time network flow algorithm. *Mathematical Programming*, Vol. 54, 1992, pp. 1-39.
- Blondel, Vincent D., Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. "Fast unfolding of communities in large networks." *Journal of Statistical Mechanics: Theory and Experiment* 2008, no. 10 (2008): P10008.
- Bodin, Lawrence, and Bruce Golden. "Classification in vehicle routing and scheduling." *Networks* 11, no. 2 (1981): 97-108.
- Boersch-Supan, A., Hajivassiliou, V., 1993. Smooth unbiased multivariate probability simulators for maximum likelihood estimation of limited dependent variable models. *Journal of Econometrics* 58(3), 347-368.
- Boile, M., Theofanis, S., Özbay, K., 2011. Feasibility of Freight Villages in the NYMTC Region. Freight and Maritime Program, Rutgers, the State University of New Jersey.

- Bowerman, Robert L., Paul H. Calamai, and G. Brent Hall. "The spacefilling curve with optimal partitioning heuristic for the vehicle routing problem." *European Journal of Operational Research* 76, no. 1 (1994): 128-142.
- Boyles, S. D., Waller, S. T. (2010). A mean-variance model for the minimum cost flow problem with stochastic arc costs. *Networks*, 56(3), 215-227.
- Braklow, J.W., W.W. Graham, S.M. Hassler, K.E. Peck, W.B. Powell, Interactive optimization improves service and performance for Yellow Freight System, *Interfaces* 22 (1) (1992) 147-172.
- Bray, Larry G., Chrisman Dager, and Mark L. Burton. "Willingness to pay for water transportation in the Ohio River basin." *Transportation Research Record: Journal of the Transportation Research Board* 1871, no. 1 (2004): 5-12.
- Brooks, M.R., Trifts, V., 2008. Short sea shipping in North America: understanding the requirements of Atlantic Canadian shippers. *Maritime Policy Management* 35 (2), 145–158.
- Brooks, Mary R., Sean M. Puckett, David A. Hensher, and Adrian Sammons. "Understanding mode choice decisions: A study of Australian freight shippers." *Maritime Economics & Logistics* 14, no. 3 (2012): 274-299.
- Brownstone, D., Bunch, D. S., Train, K., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. *Transportation Research Part B: Methodological* 34(5), 315-338.
- Brownstone, D., Train, K., 1999. Forecasting new product penetration with flexible substitution patterns. *Journal of Econometrics* 89 (1), 109-129.

- Buijs, P., Vis, I. F., Carlo, H. J. (2014). Synchronization in cross-docking networks: a research classification and framework. *European Journal of Operational Research*, 239(3), 593–608
- Busacker, R. G., Gowen, P. J., 1960. A procedure for determining a family of minimum-cost network flow patterns, Technical Report ORO-TP-15, Operations Research Office, The Johns Hopkins University, Bethesda, MD.
- Cao, B., Glover, F., 2010. Creating balanced and connected clusters to improve service delivery routes in logistics planning. *Journal of Systems Science and Systems Engineering*, 19(4), 453-480.
- Caplice, C. and Y. Sheffi. Combinatorial Auctions for Truckload Transportation, in Cramton, P. et al (ed.) *Combinatorial Auctions*. The MIT Press, 2006.
- Caplice, C., 1996. An optimization based bidding process: a new framework for shipper-carrier relationship. Ph.D. Dissertation. Massachusetts Institute of Technology. Cambridge, MA.
- Caplice, C., and Sheffi, Y. Combinatorial auctions for truckload transportation. *Combinatorial auctions*, Chapter 21, pp. 539-572. The MIT Press, Boston. 2006
- Caplice, C., Sheffi, Y., 2003. Optimization based procurement for transportation services. *Journal of Business Logistics*, 24(2), pp. 109-128.
- Cargo Auctions (2011). Corporate website. <http://www.cargosuccess.com/index.asp>. Accessed November 23, 2014.
- Carlsson, Fredrik. "The demand for intercity public transport: the case of business passengers." *Applied economics* 35, no. 1 (2003): 41-50.

- Cavalcante, Rinaldo A., and Matthew J. Roorda. "Shipper/carrier interactions data collection: Web-based respondent customized stated preference (WRCSP) survey." *Transport Survey Methods: Best Practice for Decision Making*, Chapter 13. Emerald Group Publishing Limited. Bingley, UK. (2013): 257-277.
- Chiang, Wen-Chyuan, Jason CH Chen, and Xiaojing Xu. "An overview of research on revenue management: current issues and future research." *International Journal of Revenue Management* 1, no. 1 (2007): 97-128.
- Chong, E. K. P., Zak S. H. 2013. *An Introduction to Optimization*. Fourth edition. John Wiley & Sons, Inc, Hoboken, New Jersey.
- Clausen, U., Goedicke, I., Mest, L., & Wohlgemuth, S. (2012). Combining simulation and optimization to improve ltl traffic. *Procedia-Social and Behavioral Sciences*, 48, 1993-2002.
- Coyle , J. J., R. A. Novack, B. J. Gibson, and E. J. Bardi. *Costing and Pricing for Transportation*. *Transportation: A supply chain perspective*, Chapter 4. 7th Edition. South-Western Cengage Learning. Mason, OH. 2011.
- Crainic, T. G. (2000). Service network design in freight transportation. *European Journal of Operational Research*, 122(2), 272-288.
- Crainic, T. G., Ricciardi, N., Storchi, G., 2009. Models for evaluating and planning city logistics systems. *Transportation Science*, 43(4), pp. 432-454.
- Dai, B., Chen, H., Yang, G. (2014) Price-setting based combinatorial auction approach for carrier collaboration with pickup and delivery requests. *Operational Research* 14(3), 361-386.

- Danielis, Romeo, and Edoardo Marcucci. "Attribute cut-offs in freight service selection." *Transportation Research Part E: Logistics and Transportation Review* 43, no. 5 (2007): 506-515.
- Dantzig, G. B. *Linear programming and extensions*. Princeton university press, Princeton NJ. 1998.
- De Angelis, L. 2011. A fall in average vehicle loads. Eurostat. European Commission. http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-SF-11-063/EN/KS-SF-11-063-EN.PDF. Accessed August 27, 2014.
- De Vries, S., and R. V. Vohra. Combinatorial auctions: A survey. *INFORMS Journal on computing*, Vol. 15, No. 3, 2003, pp. 284-309.
- DeltaBid (2014). RFP process and procurement management software: DeltaBid. <http://www.deltabid.com>. Accessed November 23, 2014.
- Desaulniers, G., Desrosiers, J. Ioachim, I., Solomon, M.M., Soumis, F., Villeneuve, D., 1998. A unified framework for deterministic time constrained vehicle routing and crew scheduling problems. In Crainic, T.G., Laporte, G. (Eds.), *Fleet Management and Logistics*. Kluwer, Boston. pp. 57–93.
- Desrosiers, J., Lübbecke, M.E., 2005. A primer in column generation. In G. Desaulniers, J. Desrosiers, M. Solomon (Eds.), *Column Generation*, New York: Springer Science + Business Media, (Chapter 1).
- Dezső, B., A. Jüttner, and P. Kovács. LEMON—an open source C++ graph template library. *Electronic Notes in Theoretical Computer Science*, Vol. 264, No. 5, 2011, pp. 23-45.
- Ding, S. Uncertain minimum cost flow problem. *Soft Computing*, 2013, pp. 1-7.

- Dondo, Rodolfo, and Jaime Cerdá. "A cluster-based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows." *European Journal of Operational Research* 176, no. 3 (2007): 1478-1507.
- EC DGET, European Commission, Directorate-General for Energy and Transport, 2006. Urban freight transport and logistics. European Communities. http://www.transport-research.info/Upload/Documents/200608/20060831_105348_30339_Urban_freight.pdf. Accessed August 10, 2012.
- Edmonds, J., and R. M. Karp. Theoretical improvements in algorithmic efficiency for network flow problems. *Journal of the ACM*, Vol.19, No. 2, 1972, pp. 248-264.
- Elmaghraby, W., and P. Keskinocak. *Combinatorial Auctions in Procurement*. Technical report, The Logistics Institute, Georgia. Institute of Technology, Atlanta, GA. 2002.
- Elmaghraby, W., Keskinocak, P., 2004. Combinatorial auctions in procurement. In Harrison, T.P., Lee, H.L., Neale, J.J. (Eds.), *The practice of supply chain management: Where theory and application converge*. International Series in Operations Research & Management Science, 62(3), 245-258. Springer US.
- Erera, A., Karacık, B., Savelsbergh, M. (2008). A dynamic driver management scheme for less-than-truckload carriers. *Computers & Operations Research*, 35(11), 3397-3411.
- Estrada, M., Robusté, F. (2009). Long-Haul Shipment Optimization for Less-Than-Truckload Carriers. *Transportation Research Record: Journal of the Transportation Research Board*, 2091(1), 12-20.

- Fan, P., Haran, J. G., Dillenburg, J., Nelson, P. C., 2006. Traffic model for clustering algorithms in vehicular ad-hoc networks. *Proceedings of the IEEE Consumer Communications and Networking Conference 2006 (CCNC2006)*, 168-172.
- Fortunato, Santo. "Community detection in graphs." *Physics Reports* 486, no. 3 (2010): 75-174.
- Freeman, L. C. A set of measures of centrality based on betweenness. *Sociometry*, Vol. 40, 1977, pp. 35-41.
- Freight Brokers USA (2014). Freight reverse auction. <http://www.freightbrokersusa.com/Reverse-Freight-Auction.asp>. Accessed November 23, 2014.
- Fries, N., de Jong, G. C., Patterson, Z., Weidmann, U., 2010. Shipper willingness to pay to increase environmental performance in freight transportation. *Transportation Research Record: Journal of the Transportation Research Board* 2168, 33-42.
- Geweke, J., Keane, M., Runkle, D., 1994. Alternative computational approaches to inference in the multinomial probit model. *The Review of Economics and Statistics* 76 (4), 609–632.
- Ghatee, M., Hashemi, S. M. (2008). Generalized minimal cost flow problem in fuzzy nature: an application in bus network planning problem. *Applied Mathematical Modelling*, 32(12), 2490-2508.
- Ghatee, M., Hashemi, S. M. (2009a). Optimal network design and storage management in petroleum distribution network under uncertainty. *Engineering Applications of Artificial Intelligence*, 22(4), 796-807.

- Ghatee, M., Hashemi, S. M. (2009b). Application of fuzzy minimum cost flow problems to network design under uncertainty. *Fuzzy sets and systems*, 160(22), 3263-3289.
- Ghatee, M., Hashemi, S. M. (2009b). Application of fuzzy minimum cost flow problems to network design under uncertainty. *Fuzzy sets and systems*, 160(22), 3263-3289.
- Gilbride, T. J., Lenk, P. J., Brazell, J. D. 2008. Market share constraints and the loss function in choice-based conjoint analysis. *Marketing Science* 27(6), 995-1011.
- Girvan, Michelle, and Mark EJ Newman. "Community structure in social and biological networks." *Proceedings of the National Academy of Sciences* 99, no. 12 (2002): 7821-7826.
- Gkritza, K., Mannering, F., 2008. Mixed logit analysis of safety-belt use in single- and multi occupant vehicles. *Accident Analysis and Prevention* 40, 443-451.
- Goldberg, A. V., and R. E. Tarjan. Finding minimum-cost circulations by canceling negative cycles. *Journal of the ACM* Vol. 36, No. 4, 1989, pp. 873-886.
- Guerriero, Francesca, Giovanna Miglionico, and Filomena Olivito. "Revenue management policies for the truck rental industry." *Transportation Research Part E: Logistics and Transportation Review* 48, no. 1 (2012): 202-214.
- Hejazi, B., Haghani, A. (2007). Dynamic decision making for less-than-truckload trucking operations. *Transportation Research Record: Journal of the Transportation Research Board*, 2032(1), 17-25.
- Hensher, D.A., Puckett, S. M., Rose, J. M. 2007. Agency decision making in freight distribution chains: revealing a parsimonious empirical strategy from alternative behavioural structures, *Transportation Research B*. 41 (9), 924-949.

- Hensher, David A. "A practical approach to identifying the market potential for high speed rail: a case study in the Sydney-Canberra corridor." *Transportation Research Part A: Policy and Practice* 31, no. 6 (1997): 431-446.
- Hernández, S., Peeta, S. (2011). Centralized Time-Dependent Multiple-Carrier Collaboration Problem for Less-Than-Truckload Carriers. *Transportation Research Record: Journal of the Transportation Research Board*, 2263(1), 26-34.
- Hernández, S., Peeta, S., Kalafatas, G. (2011). A less-than-truckload carrier collaboration planning problem under dynamic capacities. *Transportation Research Part E: Logistics and Transportation Review*, 47(6), 933-946.
- Hernández, S., Unnikrishnan, A., Awale, S. S. (2012). Centralized Carrier Collaboration Multihub Location Problem for Less-Than-Truckload Industry. *Transportation Research Record: Journal of the Transportation Research Board*, 2269(1), 20-28.
- Hernández-Pérez, H., Salazar-González, J. J., 2009. The multi-commodity one-to-one pickup-and-delivery traveling salesman problem. *European Journal of Operational Research*, 196, pp. 987–995.
- Hess, Stephane, Thomas Adler, and John W. Polak. "Modelling airport and airline choice behaviour with the use of stated preference survey data." *Transportation Research Part E: Logistics and Transportation Review* 43, no. 3 (2007): 221-233.
- Hung, Y. F., Chen, W. C., 2011. A heterogeneous cooperative parallel search of branch-and-bound method and taboo search algorithm. *Journal of Global Optimization*, 51(1), pp. 133-148.

- Iman, R. L., J. C. Helton, and J. E. Y. Campbell An approach to sensitivity analysis of computer models, Part 1. Introduction, input variable selection an preliminary variable assessment *Journal on Quality Technology*, Vol. 13, No. 3. (1981), pp. 174-183.
- Information Technology at Purdue (ITAP), 2014. Qualtrics Survey Software. Purdue University. <https://www.itap.purdue.edu/learning/tools/qualtrics/>. Accessed in Apr. 29th 2014.
- Iri, M. A new method of solving transportation-network problems. *Journal of the Operations Research Society of Japan* Vol. 3, 1960, pp. 27-87.
- Jara-Diaz, S. R., 1981. Transportation cost functions: a multiproducts approach. Ph.D.
- Jara-Diaz, S. R., 1983. Freight transportation multioutput analysis. *Transportation Research*, Vol. 17A(6), 429-438.
- Jarrah, A. I., Johnson, E., & Neubert, L. C. (2009). Large-scale, less-than-truckload service network design. *Operations Research*, 57(3), 609-625.
- Jewell, W.S., Optimal flow through networks, Interim Technical Report No. 8, Operations Research Center, MIT, Cambridge, MA. 1958.
- Keaton, M. H. (1993). Are there economies of traffic density in the less-than-truckload motor carrier industry? An operations planning analysis. *Transportation Research Part A: Policy and Practice*, 27(5), 343-358.
- Kelly, D. J., and G. M. O'Neill. The minimum cost flow problem and the network simplex solution method. PhD dissertation. University College Dublin, Graduate School of Business, 1991.

- Király, Z., and P. Kovács, Efficient implementations of minimum-cost flow algorithms. *Acta Univ. Sapientiae, Informatica*, Vol. 4 No. 1, 2012, pp. 67-118.
- Klein, M. A primal method for minimal cost flows with applications to the assignment and transportation problems. *Management Science* Vol. 14, No. 3, 1967, pp. 205-220.
- Ledyard, J. O., M. Olson, D. Porter, J. A. Swanson, and D. P. Torma. The first use of a combined-value auction for transportation services. *Interfaces*, Vol. 32, No. 5, 2002, pp. 4-12.
- Lee, C. G., R. H. Kwon, and Z. Ma. A carrier's optimal bid generation problem in combinatorial auctions for transportation procurement. *Transportation Research Part E: Logistics and Transportation Review* Vol. 43, No. 2, 2007, pp.: 173-191.
- Li, Z., Hensher, D. A. 2012. Accommodating risk attitudes in freight transport behaviour research, *Transport Reviews* 32 (2), 221-239.
- Lin, C. C. (2001). The freight routing problem of time-definite freight delivery common carriers. *Transportation Research Part B: Methodological*, 35(6), 525-547.
- Lin, C. C. (2004). Load planning with uncertain demands for time-definite freight common carriers. *Transportation Research Record: Journal of the Transportation Research Board*, 1873(1), 17-24.
- Lin, C. C., Chen, S. H. (2004). The hierarchical network design problem for time-definite express common carriers. *Transportation Research Part B: Methodological*, 38(3), 271-283.
- Lin, C. C., Lin, D. Y., Young, M. M. (2009). Price planning for time-definite less-than-truckload freight services. *Transportation Research Part E: Logistics and Transportation Review*, 45(4), 525-537.

- Lin, Cheng-Chang, Dung-Ying Lin, and Melanie M. Young. "Price planning for time-definite less-than-truckload freight services." *Transportation Research Part E: Logistics and Transportation Review* 45, no. 4 (2009): 525-537.
- Liu, S. T., Kao, C. (2004). Network flow problems with fuzzy arc lengths. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 34(1), 765-769.
- Ma, Z., Kwon, R. H., Lee, C., 2010. A stochastic programming winner determination model for truckload procurement under shipment uncertainty. *Transportation Research Part E: Logistics and Transportation Review*, 46(1), pp. 49-60.
- Masiero, L., Hensher, D. A. 2010. Analyzing loss aversion and diminishing sensitivity in a freight transport stated choice experiment, *Transportation Research Part A: Policy and Practice* 44 (5), 349-358.
- Masiero, L., Hensher, D. A. 2011. Shift of reference point and implications on behavioral reaction to gains and losses, *Transportation*, 38 (2), 249-271
- Masiero, L., Hensher, D. A. 2012. Freight transport distance and weight as utility conditioning effects on a stated choice experiment. *Journal of Choice Modelling* 5 (1), 64-76.
- McFadden, D., Ruud, P., 1994. Estimation by simulation. *Review of Economics and Statistics* 76 (4), 591–608.
- McGill, Jeffrey I., and Garrett J. Van Ryzin. "Revenue management: Research overview and prospects." *Transportation science* 33, no. 2 (1999): 233-256.
- McKay, Michael D., Richard J. Beckman, and William J. Conover. "Comparison of three methods for selecting values of input variables in the analysis of output from a computer code." *Technometrics* 21, no. 2 (1979): 239-245.

- Melab, N., Chakron, I., Mohand, M., Tuytens, D., 2012. A GPU-accelerated branch-and-bound algorithm for the flow-shop scheduling problem. 14th IEEE International Conference on Cluster Computing. <http://arxiv.org/abs/1208.3933>. Accessed February 15, 2013.
- Mesa-Arango, R., Ukkusuri, S. V., 2013. New trends in transportation procurement. <http://web.ics.purdue.edu/~rmesaara/Survey/home.htm>. Accessed in Feb. 2nd 2014.
- Metropolis, Nicholas, and Stanislaw Ulam. "The monte carlo method." *Journal of the American statistical association* 44, no. 247 (1949): 335-341.
- Moore E. W., J. M. Warmke, and L. R. Gorban. The indispensable role of management science in centralizing freight operations at Reynolds Metals Company. *Interfaces*, Vol. 21, No. 1, 1991, pp. 107-129.
- Nadarajah, S., Bookbinder, J. H. (2013). Less-Than-Truckload carrier collaboration problem: modeling framework and solution approach. *Journal of Heuristics*, 19(6), 917-942.
- Nagle, T. T., J. E. Hogan, and J. Zale. *The strategy and tactics of pricing: A guide to growing more profitably*. 5th Edition. Prentice Hall. Boston. 2011.
- Nejad, M. M., Mashayekhy, L., Chinnam, R. B., 2012. Effects of traffic network dynamics on hierarchical community-based representations of large road networks. *Proceedings of 15th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 1900-1905.
- Newman, M. E. J., 2003. The structure and function of complex networks. *SIAM review* 45(2), 167-256.
- Newman, M. *Networks: an introduction*. Oxford University Press, 2010.

- OECD, Organisation for Economic Co-Operation and Development, 2003. Delivering the goods. 21st century challenges to urban goods transport. <http://www.internationaltransportforum.org/Pub/pdf/03DeliveringGoods.pdf>. Accessed August 10, 2012.
- Orlin, J. B. A faster strongly polynomial minimum cost flow algorithm. *Operations research*, Vol. 41, No. 2, 1993, pp. 338-350.
- O'Rourke, Laurence. "Impact of differential pricing on barge freight transportation." *Transportation Research Record: Journal of the Transportation Research Board* 1820, no. 1 (2003): 11-16.
- Özdamar, Linet, and Onur Demir. "A hierarchical clustering and routing procedure for large scale disaster relief logistics planning." *Transportation Research Part E: Logistics and Transportation Review* 48, no. 3 (2012): 591-602.
- Özkaya, Evren, Pınar Keskinocak, V. Roshan Joseph, and Ryan Weight. "Estimating and benchmarking Less-than-Truckload market rates." *Transportation Research Part E: Logistics and Transportation Review* 46, no. 5 (2010): 667-682.
- Patterson, Z., Ewing, G. O., Haider, M. 2010. How different is carrier choice for third party logistics companies?. *Transportation Research Part E: Logistics and Transportation Review* 46 (5), 764-774.
- Porter, D., Torma, D. P., Ledyard, J. O., Swanson, J. A., Olson, M., 2002. The first use of a combined-value auction for transportation services. *Interfaces*, 32(5), pp. 4–12.
- Powell, W.B. A local improvement heuristic for the design of less-than-truckload motor carrier networks, *Transportation Science* 20 (4) (1986) 246-357.

- Powell, W.B., Y. Sheffi, Design and implementation of an interactive optimization system for the network design in the motor carrier industry, *Operations Research* 37 (1) (1989) 12-29.
- Powell, W.B., Y. Sheffi, The load-planning problem of motor carriers: problem description and a proposed solution approach, *Transportation Research A: Policy and Practice* 17 (6) (1983) 471-480.
- Psaraftis, H. N., 2011. A multi-commodity, capacitated pickup and delivery problem: The single and two-vehicle cases. *European Journal of Operational Research*, 215, pp. 572–580.
- Puckett, S. M., Hensher, D. A. 2008. The role of attribute processing strategies in estimating the preferences of road freight stakeholders under variable road user charges, *Transportation Research E: Logistics and Transportation Review* 44 (5), 379-395.
- Puckett, S. M., Hensher, D. A. 2009. Revealing the extent of process heterogeneity in choice analysis: An empirical assessment, *Transportation Research Part A: Policy and Practice* 43 (2), 117-126
- Puckett, Sean M., David A. Hensher, Mary R. Brooks, and Valerie Trifts. "Preferences for alternative short sea shipping opportunities." *Transportation Research Part E: Logistics and Transportation Review* 47, no. 2 (2011): 182-189.
- Qiong, L., Jie, Y., Jinfang, Z. 2011. Application of clustering algorithm in intelligent transportation data analysis. In *Information and Management Engineering* (pp. 467-473). Springer Berlin Heidelberg.

- Randall, W. S., C. C. Defee, and S. P. Brady. Value propositions of the US trucking industry. *Transportation Journal*, Vol. 49, No. 3, 2010, pp. 5-23.
- Research and Innovative Technology Administration (RITA)., 2013. Pocket Guide to Transportation 2013. Bureau of Transportation Statistics. U.S. Department of Transportation. Washington D.C.
- Rieck, J., Zimmermann, J. (2009). A hybrid algorithm for vehicle routing of less-than-truckload carriers. In *Metaheuristics in the Service Industry* (pp. 155-171). Springer Berlin Heidelberg
- Röck, H. Scaling techniques for minimal cost network flows. *Discrete Structures and Algorithms*, pp. 181–191, Munchen, Carl Hanser. 1980.
- Roorda, Matthew J., Rinaldo Cavalcante, Stephanie McCabe, and Helen Kwan. "A conceptual framework for agent-based modelling of logistics services." *Transportation Research Part E: Logistics and Transportation Review* 46, no. 1 (2010): 18-31.
- Sandholm, T., 2002. Algorithm for optimal winner determination in combinatorial auctions. *Artificial Intelligence*, pp. 135, 1-54.
- Sarimveis, H., Patrinos, P., Tarantilis, C. D., & Kiranoudis, C. T. (2008). Dynamic modeling and control of supply chain systems: A review. *Computers & Operations Research*, 35(11), 3530-3561.
- Sathaye, N., Y. Li, A. Horvath, S. Madanat, 2006. The environmental impacts of logistics systems and options for mitigation. Working Paper VWP-2006-4. U.C. Berkeley Center for Future Urban Transport, A Volvo Center of Excellence.

- Scherrer, A., Blondel, V. 2014. The Louvain method for community detection in large networks. Université catholique de Louvain, Louvain-la-Neuve, Belgium. 2011. <http://perso.uclouvain.be/vincent.blondel/research/louvain.html>. Accessed August 26, 2014.
- Schönberger, J., 2006. Operational freight carrier planning: basic concepts, optimization models and advanced memetic algorithms. Springer.
- SciQuest (2014). Transportation sourcing and procurement. <http://www.sciquest.com/solutions/sourcing/sciquest-advanced-sourcing-optimizer/industries/transportation>. Accessed November 23, 2014.
- Setar, L., 2013a. IBISWorld Industry Report 48412: Long-Distance Freight Trucking in the US. IBISWorld Inc.
- Setar, L., 2013b. IBISWorld Industry Report 48411: Local Freight Trucking in the US. IBISWorld Inc.
- Shah, N., Brueckner, J. K., 2012. Price and frequency competition in freight transportation. *Transportation Research Part A: Policy and Practice* 46 (6), 938-953.
- Shah, Nilopa, and Jan K. Brueckner. "Price and frequency competition in freight transportation." *Transportation Research Part A: Policy and Practice* 46, no. 6 (2012): 938-953.
- Sharman, B. W., Roorda, M. J. 2011. Analysis of freight global positioning system data. *Transportation Research Record: Journal of the Transportation Research Board*, 2246, 83-91.
- Sheffi, Y. Combinatorial auctions in the procurement of transportation services. *Interfaces* Vol. 34, No. 4, 2004, pp. 245-252.

- Sheffi, Y., 2012. *Logistics clusters: Delivering value and driving growth*. MIT Press. Cambridge, MA.
- Sheffi, Y., 2013. Logistics-intensive clusters: global competitiveness and regional growth. In *Handbook of Global Logistics*, 463-500. Springer New York.
- Shi, N., Song, H., Powell, W. B. (2014). The dynamic fleet management problem with uncertain demand and customer chosen service level. *International Journal of Production Economics*, 148, 110-121.
- Simão, H. P., Day, J., George, A. P., Gifford, T., Nienow, J., & Powell, W. B. (2009). An approximate dynamic programming algorithm for large-scale fleet management: A case application. *Transportation Science*, 43(2), 178-197.
- Simchi-Levi, D., Chen, X., Bramel, J., 2005. *The logic of logistics. Theory, Algorithms, and Applications for Logistics and Supply Chain Management*. Springer.
- Singh, G., Wenning, B. L., Becker, M., Timm-Giel, A., Gorg, C., 2007. Agent-based clustering approach to transport logistics. *Proceedings of 2007 IEEE International Conference on Service Operations and Logistics, and Informatics, SOLI 2007*, 466-471.
- SMC3 (2006). The secret of our LTL bid success. [http://www.smc3.com/smc3/knowledge-center/successstories/B\\$ns_MeadWestvaco_v3d_Pi11128-L_SnglPgs.pdf](http://www.smc3.com/smc3/knowledge-center/successstories/B$ns_MeadWestvaco_v3d_Pi11128-L_SnglPgs.pdf). Accessed November 23, 2014.
- Smilowitz, K. R., Atamtürk, A., Daganzo, C. F., 2003. Deferred item and vehicle routing within integrated networks. *Transportation Research Part E*, 39, pp. 305-323.

- Song, J., and A. Regan. Approximation algorithms for the bid construction problem in combinatorial auctions for the procurement of freight transportation contracts. *Transportation Research Part B: Methodological*, No. 39, Vol. 10, 2005, pp. 914-933.
- Song, J., and A. Regan. Combinatorial auctions for transportation service procurement: The carrier perspective. *Transportation Research Record: Journal of the Transportation Research Board* No. 1833, Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 40-46.
- Stein, Michael. "Large sample properties of simulations using Latin hypercube sampling." *Technometrics* 29, no. 2 (1987): 143-151.
- Stern, S., 1997. Simulation-based estimation. *Journal of Economic Literature* 35(4), 2006-2039.
- Street, D. J., Burgess, L., 2007. *The Construction of Optimal Stated Choice Experiments: Theory and Methods*. Wiley, New York.
- Tarjan, R. Depth-first search and linear graph algorithms. *SIAM journal on computing*, Vol. 1, No. 2, 1972, pp. 146-160.
- TFL, Transport for London, 2007. London freight plan – Sustainable freight distribution: A plan for London. <http://www.tfl.gov.uk/microsites/freight/documents/London-Freight-Plan.pdf>. Accessed August 10, 2012.
- Tomizawa, N. On some techniques useful for solution of transportation network problems. *Networks* Vol. 1, No. 2, 1971, pp. 173-194.
- Topaloglu, H., Powell, W. B. (2006). Dynamic-programming approximations for stochastic time-staged integer multicommodity-flow problems. *INFORMS Journal on Computing*, 18(1), 31-42.

- Toptal, Ayşegül, and Safa Onur Bingöl. "Transportation pricing of a truckload carrier." *European Journal of Operational Research* 214, no. 3 (2011): 559-567.
- Train, K., 1999. Halton sequences for mixed logit. Working Paper, University of California Berkley, Department of Economics.
- Train, K., 2003. *Discrete choice methods with simulation*. Cambridge University Press. Cambridge, UK.
- Train, K., 2009. *Discrete choice methods with simulation*. 2nd Edition Cambridge University Press. New York.
- Train, Kenneth, and Wesley W. Wilson. "Estimation on stated-preference experiments constructed from revealed-preference choices." *Transportation Research Part B: Methodological* 42, no. 3 (2008): 191-203.
- Transportation Topics, 2011. Total Fleets - TTNews. <http://www.ttnews.com/adrates/ttnews/TTDemographics2011.ppt>. Accessed in Apr. 22nd 2014.
- USDOT, U.S. Department of Transportation, 2012. *National Transportation Statistics*. Research and Innovative Technology Administration. Bureau of Transportation Statistics. Washington, DC. http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_statistics/index.html. Accessed September 29, 2014.
- VICS, Voluntary Interindustry Commerce Solutions, 2009. *National Filling Empty Miles for Sustainability and Savings*. http://macysgreenliving.com/media/_CustomMedia/EmptyMiles_cs_092809.pdf. Accessed August 26, 2014.

- VICS, Voluntary Interindustry Commerce Solutions, 2014. VICS (Empty Miles). GS1 North America. <https://www.emptymiles.org/>. Accessed August 26, 2014.
- Wang, X., and M. Xia. Combinatorial bid generation problem for transportation service procurement. *Transportation Research Record: Journal of the Transportation Research Board* No. 1923, Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 189-198.
- Wang, Xiubin, and Mu Xia. "Combinatorial bid generation problem for transportation service procurement." *Transportation Research Record: Journal of the Transportation Research Board* 1923, no. 1 (2005): 189-198.
- Washington, S., Karlaftis, M., Mannering, F., 2010. *Statistical and Econometric Methods for Transportation Data Analysis*. 2nd Edition Chapman and Hall/CRC, Boca Raton, Florida.
- Xu, N., Yu, C., Zhang, L., & Liu, P. (2009, August). Profit allocation in collaborative less-than-truckload carrier alliance. In *Automation and Logistics, 2009. ICAL'09. IEEE International Conference on* (pp. 258-263). IEEE.
- Yu, W., Ding, W., Liu, K., 2005. The planning, building and developing of logistics parks in China: review of theory and practice. *Chin-USA Business Review* 4(3), 73–78.
- Zamparini, Luca, John Layaa, and Wout Dullaert. "Monetary values of freight transport quality attributes: A sample of Tanzanian firms." *Journal of Transport Geography* 19, no. 6 (2011): 1222-1234.

VITA

Rodrigo Mesa-Arango is a motivated and ambitious researcher with strong foundations in mathematical programming, algorithms design, and behavioral modeling. Freight transportation and logistics is the core of his research. In his PhD he developed significant contributions in the area of revenue management for trucking services. Moreover, he has experience in several transportation research projects related to network modeling, traffic assignment, disaster management, economics, and transportation planning. With several publications and presentations in prestigious conferences, he is determined to continue developing high-quality research for the benefit of society. Rodrigo finished his PhD at Purdue University after completing his Master's degree at Universidad Nacional de Colombia, the same university where he obtained his bachelor's degree in Civil Engineering. Each degree had the same focus: Transportation. He has worked as research assistant for the Interdisciplinary Transportation Modeling and Analytics Lab at Purdue, teaching assistant for CE 398 also at Purdue. Likewise, he was part of the research group VITRA at Universidad Nacional de Colombia and he also worked as public servant for the Medellin city hall in his home country Colombia.

PUBLICATIONS

- Peer-Reviewed Journal Publications

Mesa-Arango, R., and Ukkusuri, S. V. Attributes Driving the Selection of Trucking Services and the Quantification of the Shipper's Willingness to Pay". *Transportation Research Part E: Logistics and Transportation Review*, Vol. 71, 2014, pp. 142-158.

Mesa-Arango, R., Zhan, X., Ukkusuri, S. V., and Mitra, A. Direct Transportation Economic Impacts of Highway Network Disruptions Using Public Data from the United States. *Journal of Transportation Safety & Security*, Accepted for Publication, 2014.

Mesa-Arango, R., and Ukkusuri, S. V. Benefits of In-Vehicle Consolidation in Less than Truckload Freight Transportation Operations. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 60, 2013, pp. 113-125.

Mesa-Arango, R., Ukkusuri, S. V., and Sarmiento, I. Network Flow Methodology for Estimating Empty Trips in Freight Transportation Models. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2378, 2013, pp. 110-119.

Mesa-Arango, R., and Ukkusuri, S. V. Modeling the Car-Truck Interaction in a System Optimal Dynamic Traffic Assignment Model. *Journal of Intelligent Transportation System*, Vol. 18, No. 4, 2014, pp. 327-338.

Hasan, S., Mesa-Arango, R., and Ukkusuri, S. V. A Random-Parameter Hazard-Based Model to Understand Household Evacuation Timing Behavior. *Transportation Research Part C: Emerging Technologies*, Vol. 27, 2013, pp. 108-116.

Mesa-Arango, R., Hasan, S. Ukkusuri, S. V. and Murray-Tuite, P. Household-Level Model for Hurricane Evacuation Destination Type Choice Using Hurricane Ivan Data. *Natural Hazards Review*, Vol. 14, No. 1, 2013, pp. 11-20.

Hasan, S., Mesa-Arango, R. Ukkusuri, S. V. and Murray-Tuite, P. Transferability of Hurricane Evacuation Choice Model: Joint Model Estimation Combining Multiple Data Sources. *ASCE Journal of Transportation Engineering*, Vol. 138, No. 5, 2012, pp. 548-556.

- Peer-Reviewed Conference Papers with Proceedings

Mesa-Arango, R., and Ukkusuri, S. V. Benefits of In-Vehicle Consolidation in Less than Truckload Freight Transportation Operations. 20th International Symposium on Transportation and Traffic Theory (ISTTT20). *Procedia-Social and Behavioral Sciences*, Vol. 80, 2013, pp. 576-590.

Mesa-Arango, R., Ukkusuri, S. V., And Sarmiento, I. Network Flow Methodology for Estimating Empty Trips in Freight Transportation Models. 92nd Annual Meeting of the Transportation Research Board (TRB). *Compendium of Papers. Current Research in Freight Transportation and Logistics Planning Operations* No. 248, 2013, Paper 13-4684.