UNIVERSITY OF BERGAMO

School of Doctoral Studies
Doctoral degree in Analytics for Economics and Business
XXXII Cycle
SSD: Operations research

TITLE:

OPTIMIZATION PROBLEMS FOR FREIGHT FORWARDING COMPANIES

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Doctor thesis

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Academic year 2018/2019

Abstract

The ever increasing international trade led in the last decade to a steady, but constant, growth of demand for international transport. At the same time, technology developments permit safer and cheaper transportation services, allowing companies to broad their markets by reaching customers all over the globe. The rise of e-commerce and the global spread of production generated the need for fast worldwide deliveries, only possible with the use of air transportation. Moving goods between different countries is a complex activity that requires the coordination of multiple actors, successively offering various specialized services. In the given setting, freight forwarding companies play a key role and are one the main figures in international multimodal transportation. Shipper companies are rarely capable of handling this kind of operations by themselves and, thus, they rely on the know-how of specialized suppliers and forwarding agents.

Despite their relevance, freight forwarders problems have not been much investigated by the literature in transportation. Organizing a large number of shipments is a complex task and the potential for optimization is significant in many aspects of the activity.

This PhD thesis analyze multiple aspects of the problems encountered daily by freight forwarding companies.

The first problem approached is the organization of numerous shipments. A mixed integer linear programming (MILP) formulation of the problem is presented, implementing multiple operational aspects. Real world data is used to generate instances in order to validate the effectiveness of the model and get managerial insights on the company activity. A matheuristic approach is successively developed to improve the solutions found by the MILP formulation. Heuristics are used to enhance the performance of the approach, finding faster, and in some case, better solutions.

Another problem tackled in the thesis is the consolidation of multiple loose packages into transport units (e.g. pallets) with the objective of optimizing the layout for air transportation. Characteristics typical of air transportation are taken into account to identify solutions valuable for real applications. The proposed algorithm

and local searches are applied to benchmark instances and the preliminary results are presented and analyzed.

Acknowledgements

First and foremost, my greatest and sincerest thanks goes to my supervisor, Prof. Claudia Archetti, for the infinite patience and unending support given during the PhD course, for answering every question, for all the enlightening advices and for the invaluable guidance.
I am extremely grateful to Prof. Enrico Angelelli for introducing me to the fine art of being accurate and precise in my research, for teaching me how to approach problems in advance and for showing me the expertise necessary to tackle difficult problems.
My deepest thanks goes to Prof. M. Grazia Speranza for the precious insights on the depths of Operations Research and for teaching me how to handle multiple aspects of a problem and to always look to the big picture.
Thanks to all the colleagues at the department of OR at the university of Brescia, your company made fighting with obstacles much lighter.

A special thanks goes to the XXXII cycle crew and to the settlers of office CCVI, you made the last three years absolutely terrific and the local fairs we hosted at the university redifined the state of the art of parties to a whole new level.
I am honored to not call you colleagues, but friends.

Thanks to my parents for the unconditional support always given during my life, I love you.

Ringraziamenti

I miei più grandi e sinceri ringraziamenti sono rivolti al mio supervisor, Prof. Claudia Archetti, per l'infinita pazienza e il supporto inesauribile dato durante il corso del dottorato, per aver risposto ad ogni domanda, per gli illuminanti consigli e per la guida inestimabile.
Sono estremamente grato al Prof. Enrico Angelelli per avermi mostrato come essere preciso e meticoloso in ogni aspetto della ricerca, per avermi insegnato ad anticipare l'insorgere di certi problemi e per l esempio di competenza necessaria per affrontare problemi di natura complessa.
Profondi ringraziamenti vanno alla Prof. M. Grazia Speranza per la preziosa visione sulla profondità della ricerca operativa e per avermi insegnato come approcciare i molteplici aspetti di un problema e di ricercarne la visione generale.
Grazie ai colleghi del dipartimento di Ricerca Operativa dell'Università degli Studi di Brescia, la vostra compagnia ha reso leggere giornate estremamente pesanti.

Un ringraziamento speciale va alla ciurma del ciclo XXXII e ai coloni dell'ufficio CCVI, avete reso questi tre anni assolutamente straordinari e le fiere ospitate in università hanno definito un nuovo benchmark in materia di feste.
Sono onorato di non chiamarvi colleghi, ma bensì amici.

Grazie ai miei genitori per il supporto incondizionato donatomi durante l'arco della vita, vi voglio bene.

Contents

Chapter 1

Introduction

International trade is in constant growth. According to ITF 2017 statistics, global GDP grew by 3.8% in 2017 with respect to the previous year, which lead to an increase in world trade of 3.6%. In particular, air transportation registered an increase of 9% in traffic. Freight transportation using air modality is expected to increase at higher rates in the years to come, with a predicted average growth of 5.5% per year until 2030, the highest between transportation modalities (maritime is expected to grow approximately by 3% per year between 2017 and 2030). There are three main reasons explaining this trend. First, current global inventory restocking cycles are focused on minimizing the amount of material in stock and implements just-in-time deliveries. Any unexpected rise of the demand will lead to a shortage and, thus, fast transportation solutions are required. Second, air transportation move approximately 90% of the business-to-consumer e-commerce goods. It is reasonable to assume that e-commerce will keep growing in the years to come, and the demand for fast transport solutions with it. Last, air transportation is a fast, very expensive modality when compared with other means of transportation. It has always been used for transporting goods for which delivery time is essential (perishable goods, pharmacological, biological, etc.) or with very high value. With developing countries becoming richer, an increase of transportation of high value products having them as destination is to be expected. China and the Far East area accounted for 40% of total air transportation, and freight moved by air to Africa increased by 25.2%.

In this setting, a prominent figure in international freight transportation are freight forwarding companies. Freight forwarders organize shipments for individuals or corporations to get goods from the manufacturer or producer to a market, customer or final point of distribution. Freight forwarders need to relate with multiple carriers

in order to move the goods from origins to destinations and assist customers during the preparation of the required documentation, especially during customs operations. International transportation is a complex system requiring the coordination of multiple actors exchanging a wide set of documents and informations, therefore most of the times shipper companies prefer to focus on their core business and leave logistics and trasportation issues in the hands of professional third parties. This is motivated, moreover, by the fact that aviation technological infrastructure is not as well developed as in other modalities and harmonization between different countries is far from being a reality. Thus, a network of forwarding agencies spread throughout the globe is mandatory to ensure the smooth transportation of shipments. The activity of freight forwarders rely heavily on such a structure of specialized agents, and with that they can offer professional assistance in every corner of the world.
Despite the key role played in international freight transportation, freight forwarders problems have rarely been studied in the literature. Scope of the thesis is to introduce the Air Transportation Freight Forwarder Service Problem (ATFFSP) where a freight forwarding company need to select the best set of transportation services to use, and which shipments has to be consolidated together, in order to fulfill customer requests, with the objective to minimize the total cost. A mixed integer linear programming (MILP) formulation of the problem is presented. Real world data is used to generate instances of multiple size, which are then solved by the model using CPLEX. The results shows difficulties encountered by the model for large size instances, where the number of available options increases sensibly and CPLEX runs out of memory. To comply with the issue, a matheuristic approach is proposed, which is based on the construction of feasible routes for shipments, from origin to destination.
Freight forwarders usually offers logistics services to their customer. One activity is the palletization of loose packages. Dimensions, weight and number of pallets directly influences the cost of air transportation and in some cases restrain the selection of possible services that can be used. Not always a lower number of pallets is a better option since multiple aspects are considered in the calculation of the taxable weight applied by companies. In the last chapter of the thesis a three dimensional bin packing algorithm is introduced in order to optimize this operation.

1.1 Outline of the thesis

The thesis introduces the ATFFSP, tackling the operative problem, challenged daily by freight forwarders, of choosing the best set of services in order to carry out the transportation service requests coming from customers.

The thesis present in Chapter 2 a survey on optimization problems on multimodal transportation in general. For each combination of modes, the recent trends in literature are shown, and the possible future developments are proposed.
Freight forwarders who operates in air transportation are forced on using multimodal transportation and thus, in Chapter 3, it is introduced the ATFFSP. The aim of the problem is to select the best set of services to be used in order to ship customers transportation requests. The MILP formulation of the problem is presented and exact solutions are found by means of the commercial mathematical programming solver CPLEX. Real world data are used to study the effectiveness of the model and managerial insights are given. Results are compared with the solution adopted by an italian freight forwarding company, which made the real world data available. The model is proved to be effective on solving to optimality small and medium size instances, while for big size instances some issues are encountered.
To overcome the problems in finding good solutions for big size instances as highlighted in Chapter 3, a matheuristics method to solve the ATFFSP is explored in Chapter 4. The matheuristics are based on a set-partitioning formulation where the variables represents complete routes from origin to destination. Complete enumeration of all the feasible routes yields bad results and, therefore, acceleration techniques are developed in order to reduce the number of routes considered while preserving optimality conditions. Despite the effectiveness of such techniques is proved, a heuristic approach is needed to improve the results of the MILP formulation.
Chapter 5 present a three dimensional bin packing problem (3D-BPP) directly related to the activity of freight forwarders. Availability and cost of air services depends heavily on the characteristics of the shipment. Consolidation of loose packages in transportation units such as pallets is a fundamental logistics activity for freight forwarding companies. The usual objective of 3D-BPP is the minimization of the units used to consolidate loose packages. The algorithm proposed try to minimize an objective function that consider the cost of air transportation service and optimize the balance of the transport units used. Benchmark instances are solved and preliminary results are investigated.

1.1.1 Chapter 2: Optimization in Multimodal Distribution Problems: A Survey

Thanks to globalization the international trade grew rapidly and constantly in the last 20 years. International transportation demand grew with it, to the point where

the classical unimodal road transportation became not only infeasible in case of intercontinental transports, but unsustainable for the environment and economically inconvenient.
Multimodality is the natural evolution and the future of transportation. Multimodality requires the use of complex networks where making choices is never trivial. Operational research practitioners found in transportation with multiple modes a challenging environment, dense with problems and applications. Therefore, the literature is wide and spread out between multiple industry sectors. In this chapter, a survey on the literature in multimodal transportation is presented, focusing on dividing the studies according to the modalities interested and the nature of the problem: operational, tactical or strategical. This chapter is used for the journal paper Archetti et al. (2019) to be submitted for publication.

1.1.2 Chapter 3: Air intermodal freight transportation: The freight forwarder service problem

In this chapter, the ATFFSP is introduced. The problem focus on identifying the best set of services a freight forwarder needs to activate in order to fully comply with customers transportation requests. Optimization seeks the minimization of the system total cost.
The MILP formulation of the problem is solved using a commercial solver, finding optimal solutions for the majority of the instances. Optimality gaps for greater instances are limited. Instances are generated using real world data in collaboration with an italian freight forwarding company.
The model provided solutions leading to a consistent reduction of costs when compared to the solutions adopted by the company. The same model is used to provide some managerial insights on the possibility of opening a new warehouse. This chapter lead to the journal paper Archetti and Peirano (2019) published on Omega.

1.1.3 Chapter 4: A Matheuristic for the Air Transportation Freight Forwarder Service Problem

The MILP formulation presented in Chapter 3 encounters some difficulties in finding optimal solutions for large and very large instances. Then, in this Chapter a matheuristic approach is presented. The matheuristic is based on the construction of feasible origin-destination routes for shipments, and on solving a set-partitioning formulation. Complete enumeration, acceleration techinques and an heuristic approach are analyzed for the construction of feasible routes. The same real world based instances from Chapter 3 are solved to prove the effectiveness of the methodology proposed, leading to improvements for large size instances. Heuristic solutions have a small gap with respect to the optimal solution found with the MILP formulation presented in Chapter 3. The chapter streamed in the journal paper Angelelli et al. (2019) that has been submitted for publication.

1.1.4 Chapter 5: The Air Transport Unit Consolidation Problem

Consolidating loose packages on transport units (e.g. pallets or containers) is a core activity for freight forwarders offering logistic services to their customer.
This chapter introduce a three dimensional bin packing problem with the objective of finding the optimal layout for air transportation, minimizing the cost of transportation services and ensuring stability by finding the optimal location of the center of gravity of the transport unit. The approach at first uses the Extreme Point procedure to identify a starting solution, then the solution space is explored through a bi-level local search. Tests are presented on benchmark instances for the three dimensional bin packing problem. This chapter is a work-in-progress.

1.2 Scopes and contributions

The ATFFSP is a multicommodity flow problem where the objective is to select the best set of transportation services that will be used to satisfy customers transportation requests. Shipments can be consolidated together in order to lower the unitary cost of transportation services. The objective is the minimization of the total cost given by transportation costs, stocking costs, penalties and incentives for late and early deliveries, respectively. The main contribution of this thesis is the introduction of the problem into the literature. Freight forwarders are rarely approached by the literature and, particularly regarding air transportation, their core operative problem has never been directly tackled by researchers. A MILP formulation for the model based on a time-space network is presented. The model is solved through a commercial solver. The results on real-world data shows the relevance and effectiveness of the model. By comparing the solutions found by the model with the solution adopted by the freight forwarding company that provided the data, it is shown that the presented model is capable of finding good solutions, likely to be used in real life scenarios, leading to substantial cost saving for the company.

Large instances are never solved to optimality though, and therefore a second approach is introduced. A matheuristic approach is proposed which constructs origin-destination routes for shipments, the best routes are then selected by solving a set-partitioning formulation of the problem. Acceleration techniques in the form of dominance rules applied to routes and virtual services representing the Pareto barrier are used to reduce the size of the model, preserving optimality at the same time. Moreover, heuristics are used during the generation of feasible routes. Results show that the heuristic approach is capable of returning near-optimal solutions with limited optimality gaps in fast times. For large instances the solution found is improved with respect to the MILP formulation.

Afterwards, a second fundamental activity is approached. Consolidating loose packages on transport units, e.g. pallets, is a logistic service often offered by freight forwarding companies. Dimensions and weight of the transport unit directly influences the cost of air transportation services and can potentially limit the availability of services. The thesis introduces a three-dimensional bin packing problem where the objective is to optimize the layout of consolidation in order to be suitable for air transportation.

Chapter 2

Optimization in Multimodal Distribution Problems: A Survey

Abstract

Since the rise of globalization, international trade grew constantly and the demand of transportation services grew with it. Multimodal transportation is a natural evolution of the classical unimodal road transportation, and is a mandatory choice for intercontinental shipments. Optimization techniques always found a perfect ground for applications in transportation, and the increase in the number of commodities that every year are transported all around the globe enhanced the interest and the usefulness of operational research studies. The literature in optimization in multimodal transportation is flourishing with interesting and multifaceted problems. Meanwhile, new emerging technologies generate new challenges for researchers. The scope of this survey is to provide a picture of the state of the art of the literature in optimization in multimodal transportation, for each combination of modes. In every section an overview of recently published studies is given, identifying currently ongoing topics and upflowing trends for future researches.

Keywords: Multimodal transportation, Survey, State of the art

2.1 Introduction

Freight transportation is a key aspect of the supply chain management, especially in an ever increasingly globalized economy where the consumer demand of products is geographically separated from producers location. The increase in quantities and distance of international trades, and therefore of transportation of goods, made the classical unimodal road transportation a sub-optimal solution when not an infeasible one (intercontinental transportation requires at least another modality). Moreover, recent trends in logistics research focus on environmental aspects and explore new ways to reduce emissions and negative externalities. The natural evolution of transportation is then the use of multiple modalities. To the author's knowledge, there are two main definitions of transportation with multiple modes. *Multimodal* freight transportation is often defined as the transportation of goods carried out by a sequence of at least two different modalities. Goods can be transported in various transport units (crates, pallets, cages, containers) or as loose packages loaded directly on transportation means, such as trucks, vessels, aircrafts. This is the broader and more general definition since it highlights the main features of transporting goods with multiple modalities. A more specific, often used, definition is *intermodality*. Intermodal freight transportation is defined as the transportation of goods by a sequence of at least two different modalities without changing the transportation unit during the transshipment phase from one modality to the other. In intermodality the goods are loaded at the origin place (usually the shipper warehouse) inside the transportation unit (the most common example is the containerization of goods). The transport unit is then moved, shifting between modalities, until it reaches the final delivery location, where goods are unloaded. Intermodality exploits economies of scale and hastens transshipment operations, but requires proper facilities and equipment for the handling of transportation units. Intermodal transport reverse logistics is an issue to be tackled: due to traffic and trade imbalances, some countries are mainly exporters while others are natural importers and, thus, the need rises for empty transport units to be moved from import areas back to export areas.

Despite the differences between the definitions given in the literature, the main focus of multi-modal transportation is the use of more than one modality in order to move freight from one location to another. In this work, when talking about transportation with multiple different modalities, the term *multimodal* will be used since it represents the wider and more generic definition of freight transportation with multiple modalities. Any specific definition will be used when needed, in order to better understand the setting of the study.

Multimodal transportation is divided in three phases. *Pre-haul* is the transportation from the starting location to an interchange terminal where the shipment switch modality; it is usually carried out by road transportation. *Long-haul* is the leg which covers the longer distance. Long-haul leg is carried out by means of rail, maritime, inland waterways or air transportation, is usually less expensive when compared to road transportation for long distances and is often mandatory. *End-haul* is the so-called *last mile*, i.e. the last leg to delivery location and, as in pre-haul, is carried out by road transportation in most of the cases. It is to be noticed that in long-haul it can be used more than one modality. For instance, by considering an intercontinental transportation from China to the U.S., what usually happens is that pick-up is carried out by road to the nearest multimodal exchange terminal where containers are loaded to trains directed to one port. There, the shipment is moved through a maritime service and once arrived in the U.S., depending on the delivery location, it can again be moved through a rail transportation service to a multimodal terminal from where it is delivered to the final destination by road.

Policy makers, like the European Union in the White Paper on Transport 2010, pointed out the importance of creating a transportation network capable of fostering the development of multimodality in order to decrease emissions and congestion, improving efficiency and redistributing freight transportation between modalities. Modal split, however, is still largely unbalanced in favour of road transportation. According to EUROSTAT, in 2016, across the 28 countries members of the EU, 76.4% of freight was transported by road, 17.4% by rail and the remaining 6.2% by inland waterways.

The literature in multimodal transportation is very wide and in constant growth. The goal of the current chapter is to provide a review of the literature on multimodal transportation. In particular, the aim is to explore the different problems and challenges that characterize each type of multimodal transportation. The effort focuses in classifying the literature based on the modality used in the long-haul leg. For each modality are analyzed the main decisions taken, the nature of the problems tackled (operational, tactical and strategical) and possible future fields of research are pointed out. This chapter is organized as follow. Section 2.2 presents some general information about the survey. In Section 2.3 are explored the papers where the long-leg is mainly carried out on rail, in Section 2.4 the main focus is on maritime transportation while Sections 2.5 and 2.6, respectively, consider air transportation and works where the use of more than two modalities is involved.

2.2 Overview

The survey covers 86 papers, the majority being published on journals, with a particular focus on studies published from 2014. In fact, an extensive review of the literature preceding 2014 can be found in SteadieSeifi et al. (2014). Papers published before 2014 that are considered particularly worth mentioning are included in this survey. The papers are classified based on the modality used to transport goods in the long-haul section of the shipment and on the nature of the problem tackled. Operational problems are often easy to identify, while the line between tactical and strategical problems is not always clear. Thus, the contributions are classified in operational and tactical/strategical. The majority of contributions are optimization studies where a mathematical programming problem is proposed (78 papers out of 86 contains a mathematical model, their classification is reported in Table 2.1). Other than these, the remaining papers are studies presenting interesting topics related to multimodal transportation, effective theoretical results capable of helping the solution of the most common formulations, reviews on specific topics and works of different nature which do not present optimization models but are nonetheless useful for the scope of the survey.

Table 2.1: Papers classification

Modality / Problem	Operational	Tactical	Strategical	Total
Rail	6	11	9	26
Sea	4	5	2	11
Air	16	0	1	17
Multiple	6	10	8	24

Not surprisingly, the most studied problems are the ones considering the multimodal transportation on rail (26 out of the 78 papers with a mathematical model, one third of the total). Modal shift from transportation carried out mainly by trucks to a more sustainable option, using trains, is one of the main focus of western countries policy makers and, therefore, the popularity of research in this field is not surprising. Multimodal transportation where the long-haul leg is carried out by means of air transportation saw a recent surge in optimization research due to new technologies exploring the possibility of drone deliveries (21.79%). Problems tackled by researchers in the field of multimodal transportation are very often inspired by real case applications, with a good number (50%) of papers containing real data or seeking optimization of real size instances in order to find solutions that can effectively be used in practice. Due to the practical and difficult nature of this kind of problems, the use of commercial solvers like CPLEX or GUROBI is not always viable. In fact, the majority of studies (47 out of 78, 60.26%) propose a heuristic approach or present tailored exact methods in order to efficiently find good solutions.

A final note is about the journals on which the research on multimodal transportation has been published. Due to the nature of the field of research, the largest number of papers are published on operational research, computer science and trasportation science focused journals (Transportation Research, European Journal of Operational Research, Computers & Operations Research). On the other side, the number of publications on journals not entirely focused on logistics is noticeable, with journals interested in production, industrial engineering, business and management. Table 2.2 shows an overview of the journals with more than one publication.

Table 2.2: Journals

Journal	Nř papers
Transportation Research Part E	11
Transportation Research Part B	5
European Journal of Operational Research	5
International Journal of Production Economics	4
Journal of Transport Geography	4
Procedia	3
Transportation Research Part C	3
Computers & Operations Research	3
Transportation Science	2
Computers in Industry	2
Computers & Industrial Engineering	2
Transportation Research Record	2
Other (1 paper)	40
Total	86

2.3 Long-Haul Rail Transportation

The theme of intermodal freight transportation, featuring the long-haul leg carried out by means of rail transportation, is an extremely contemporaneous and deeply studied topic. The urge of rethinking the freight transportation network is a consolidated milestone for well developed countries and the goal of reducing emissions is on top of policy makers agenda. In the White Paper 2011 the EU states *the need to drastically reduce world greenhouse gas (GHG) emissions, with the goal of limiting climate change below 2°C. Overall, the EU needs to reduce emissions by*

80-95% below 1990 levels by 2050, in the context of the necessary reductions of the developed countries as a group, in order to reach this goal. Since the transportation industry is one of the main contributors to the emissions of GHGs, a shift in the modal split in favor of rail is required.

The main drawback of multimodal rail-road transportation, when compared to unimodal road transportation, is that it requires the passage through a transshipment multimodal terminal where goods are moved from the road vehicles, usually trucks, in order to be loaded to cargo trains. This operation not only is time consuming and generates costs, but impacts negatively on the transit and delivery times when terminal operations are not carried out efficiently, with negative effects on the service level offered to customers.

Of the 26 studies considered that optimize the multimodal transportation using road and rail services, 6 tackle problems of operational nature while 11 and 9 seek optimization for tactical and strategical problems, respectively.

Two models do not presents a mathematical optimization model but instead present useful cost analysis, helpful in order to understand the cost structure of intermodality between rail and road.

A model which analyze the generalized cost of intermodal transportation by considering the multiple aspects that contributes to its amount have been proposed by Hanssen et al. (2012). Is common knowledge that due to its cost structure (higher fixed cost, infrastructural expenses and transshipment costs) intermodal transportation is more convenient with respect to an unimodal solution only if the total distance, in particular the segment of the long-haulage part of the transportation service, is relevant. In their work, the authors claim that the optimal long-haul distance in which intermodal transportation becomes preferable with respect to unimodal road transportation increases if: handling costs at terminal increase, total transportation distance increases (unimodal transportation usually has a higher kilometric cost, therefore the longer is the distance to be covered the more likely intermodality will be a better choice), pre- and post- haulage costs increase, marginal costs for rail increases, the marginal costs for truck decreases and resting costs for truck drivers are reduced. As a general rule, the higher is the impact of intermodal costs (handling, transshipment, pre- and post- haulage) or the lower is the cost of the unimodal solution, the longer needs to be the long-haul distance in order to be convenient. Another study that calculates intermodal costs is Kordnejad (2014), where the author presents a model of a regional rail based intermodal transport system. The author applies the model to a case study in order to evaluate the efficiency of the rail based distribution system in the Stockholm region. The model considers a great deal of aspects for each module contributing to the calculation of costs such as rail operations (number of locomotives and wagons, weight, emission factor, insurance and capital cost among the others), road haulage (average speed, maintenance, driver costs, interest rate) and terminal handling (infrastructural costs, shunting, transloading operators and equipment). The results indicate that the most critical parameters for such a system to be competitive are the loading space utilization of the train and the cost for terminal handling.

2.3.1 Operational problems

Operational problems focus on the management of the day to day business. The most common problem tackled is the selection of the best way to move goods through a multimodal network, where passing through transshipment terminals is mandatory to switch modality from road to rail. Optimization of network flows has been explored in Bierwirth et al. (2012), where the authors study the effect of consolidating different shipments in order to achieve a reduction of costs and an improvement of the service level. Bhattacharya et al. (2014) propose an optimization model based on arc flows in a time-space network for the same problem. Lee et al. (2014) present a linear programming model coupled with a geospatial dynamic trip assignment model. The objective of the study is to optimize an intermodal transportation flow by minimizing the total impedance given by the sum of transportation, inventory and transshipping impedances. Assadipour et al. (2015) study a shipment plan problem for hazardous material with a nonlinear formulation.

Trends and future research: Operational problems are less studied than strategical and tactical problems, and the majority of them are treated as flow optimization problems. Some works, as Kozanidis (2017) and Dayarian et al. (2015), consider vehicle routing problems (VRP) applied to pre-haul leg and end-haul leg. However, they are not combined with the long-haul leg transportation. Thus, it would be worth studying if and how VRP and flow optimization change in a combined environment where the flow decisions taken in the whole network are influenced by the solution of the VRPs at both pre-haul and end-haul legs. Also, alternative formulations other than flow formulations are worth to be explored. Intermodal transportation is characterized by the typical network configuration and therefore flow formulations are a natural representation of the problem. However, different aspects rather than the movement of commodities throughout the network, like service scheduling, to achieve better synchronization, or shipment planning problems, should be explored, especially considering an integrated network setting. More integrated systems can also consider the implementation of facilities management problems like load and unload planning operations, traffic management at transshipment terminal coordinated with operation scheduling and yard management problems.

2.3.2 Tactical and strategical problems

Tactical and strategical problems are very similar, with differences related to the time span considered for the decision and the extension/size of the problem itself. For instance, a problem can have a tactical nature if the objective is to identify a transshipment terminal with which to sign medium or long-term contracts, and strategical if the objective is to build a transshipment terminal in order to operate it for a longer period of time. In either case the problem is to identify the location of the facility. Identifying the optimal location for intermodal terminals is a prominent topic, especially since a major policy maker objective is the transfer of traffic from trucks to trains in order to reduce both emissions and congestion. Examples can be found in Limbourg and Jourquin (2009), Sörensen et al. (2012), Lin and Lin (2016), Ambrosino and Sciomachen (2014) and Ambrosino and Sciomachen (2016). Intermodal transportation inherently needs logistics networks to be efficiently used. Thus, the optimal design of both physycal networks (i.e. the creation of railway, transshipment terminals and hubs) and service networks (a set of connected rail and road services) is a highly studied topic. Interesting applications of network design can be found in Tonneau et al. (2015), Arnold et al. (2004), Zhang et al. (2013) and Karimi and Bashiri (2018). In the latter, the authors propose a multi-commodity multimodal supply chain network which is designed for intelligent manufacturing. The objective is to identify the location of the hubs where traffic flows are split between rail and road transportation. A mixed integer linear programming model is proposed to minimize the total logistics costs. Poudel et al. (2016) design a multimodal transportation network for biomass transportation, proving that an increase in use of the multimodal option can efficiently tackle supply uncertainties. Fotuhi and Huynh (2018) propose a model for the network expansion problem, solving different instances of network design in different time periods, each one influencing the successive time period.
Flows formulations are used in problems with tactical and strategical nature too. Often, the study of the flows in the network can help to identify improvements to it, or study the effects and impacts of changes in the network. Examples of flow formulations used to optimize tactical decisions can be found in Ambrosino et al. (2016) and in Ambrosino and Sciomachen (2017), where the problem is to identify the best set of investments, in order to optimize the increase of modal split favouring rail over road. Uddin and Huynh (2015) seek an a priori optimal assignment of

traffic over rail and road, in a large scale intermodal network. The same authors use a similar idea to decide how to redirect traffic in view of disruptive events in Uddin and Huynh (2016).

When the choice of the best way to move shipments through a network directly influences the design of the network itself and, at the same time, the design of the network influences the selection of the services used to ship cargo through it, then the problem studied is the so called Service Network Design (SND). Ishfaq and Sox (2012) proposes a SND problem that considers delays at hubs, while Bouchery and Fransoo (2015) implements environmental aspects in the form of carbon emissions and externality costs in the development of an intermodal network. Laaziz and Sbihi (2019) propose the problem of a freight forwarder that needs to optimize a rail-road network in order to efficiently handle a great number of shipments. No real data is used but the model solves efficiently real size instances. Nossack and Pesch (2013) propose a scheduling problem arising in intermodal transportation, where services of different modalities are coordinated in order to reduce waiting time at transshipment terminal and avoid congestion.

Trends and future research: Strategical and tactical problems involving intermodality with a combination of road and rail transportation are fairly common, and one of the first and most studied topics in the literature. Western developed countries intensify their efforts in shifting the modal split from the current situation, where road transportation is prominent, to a more sustainable intermodal solution. Henceforth, more and more studies consider environmental aspects, mainly in the form of carbon emissions. Other forms of negative externalities are not that prominent and future research should investigate efficient ways of handling transportation while effectively reducing, for instance, congestion or implementing the effect of mitigation actions. Other directions of study with high potential are related to the development of combined systems, in the form of intermodal networks in which coordinated rail and road services are offered. This would mean to enlarge the above-mentioned studies on SND to include coordinated road services. Such a coordinated system should be able to efficiently diminish carbon emissions and offer better and less expensive logistic services to customers.

Innovative forms of distributions using intermodality, with an increased use of rail, can be explored. For instance, intermodal terminal can be placed near urban areas and equipped with anything necessary to offer warehouse and distribution services in order to reduce the length of pre- and end- haul transportation. Finally, it would be worth expanding the research in new, possibly improved, layouts for intermodal networks.

2.4 Long-Haul Maritime and Waterway Transportation

According to the International Maritime Organization (IMO) roughly 90%, in weight, of global trade is carried by sea. This is due to the fact that it allows a cost effective, efficient and safe way of transporting goods. It permits the transportation of high quantities of raw materials like metal ore, wood, grain; or liquid bulk such as crude and refined oil, liquified gas, chemicals of any kind. Transportation of special material, particularly over-dimensioned or over-weighted goods, is often possible with maritime transportation only and in any case is the less expensive option. Containerized transportation is in constant growth (in 2017, according to the UNCTAD annual report, it registered a growth of +6.4%) and it is the main actor in intermodal transportation. In 2017 the total container throughput of all ports of the world summed up to 752 millions TEUs (UNCTAD 2018), with the top three ports in the world (Shanghai, Singapore, Shenzhen) accounting for 103 millions TEUs and over 1.5 billion tons moved.
International trade is inherently imbalanced, with some countries that are natural exporter of goods while others are natural importer. This is particularly evident in maritime transportation. The problem of containers reverse logistics is prominent, and is driven by the need to move empty containers from import areas back to export areas. Clearly, optimization techniques must be implemented to ensure the smooth transportation of the ever increasing quantities moved by the maritime industry.

2.4.1 Operational problems

Operational problems focus mainly on finding the optimal cargo route or the set of services needed to minimize the cost for transporting a cargo. Flow formulations are often used as in Agarwal and Ergun (2008), where the authors present an integrated model that solve both ship scheduling and cargo routing simultaneously. Heuristics are proposed in order to solve real size instances with up to 20 ports and 100 vessels. Balakrishnan and Karsten (2017) propose a multi-commodity flow problem on an augmented network with constraints on the maximum number of transshipment operations, inspired by real life applications. Zhao et al. (2016) propose a Binary Linear Programming (BLP) formulation to model a multi-commodity flow problem, seeking the optimization of the container routes in an intermodal network combined with rail services. Ayar and Yaman (2012) propose various valid inequalities and a Lagrangian relaxation approach for a multicommodity routing problem where both sea and road services are scheduled in advance. Infante et al. (2009) study a ship-truck intermodal transportation problem and introduce a heuristic to solve it.

Trends and future research: Intermodal operational problems with sea transportation and truck-rail transportation services did not receive much attention from the literature. This is mostly due to the fact that they are two separate legs of transportation, carried out by completely different actors that rarely collaborate. As already pointed out in Lam and Gu (2013), a promising field for future researches is the development of studies focused on an integrated setting where shipping companies cooperate with both ports and hinterland intermodal terminals to offer integrated, synchronized, optimized services. Cooperation between actors vertically placed along the supply chain could bring positive effects to any party involved in intermodal transportation. The use of optimization techniques should be able to prove it so. Moreover, environmental issues such as congestion, emissions and negative externalities should also be considered since benefits in these aspects are potentially higher than a pure economical analysis. An integrated and coordinated system will be capable of reducing the environmental impact of intermodal transportation, with beneficial effects for the communities.

2.4.2 Tactical and strategical problems

Maritime transportation involves activities from a wide number of different actors in order to carry out operations successfully. For this reason, it is one of the most studied field for applications of operational research since the number of problems arising is noticeable. From a tactical and strategical point of view, the problems tackled more frequently are the fleet composition problem, maritime liner problem, line fleet assignment and service network design.
The fleet composition problem seeks the optimal combination of vessels capable of satisfying the expected demand. The objective of the problem is to identify not only the number and size of vessels, but also which part of the fleet should be chartered and the duration of the chartering contract, and which part should be of owned property.
The maritime liner problem is the definition of the line service offered by the company (which ports are visited and with which frequency) and is often connected to the line fleet assignment problem, where vessels are assigned to line services. Service network design is a particular case of liner service problem and, as described further in this paragraph, it holds great potential for future researches.

Fleet deployment (Wang and Meng (2012)), cargo routing (Song and Dong (2012), Alfandari et al. (2019)), shipping network design (Plum et al. (2014), Karsten et al. (2015)) are all problems for which typically no intermodal integration is considered. One example of intermodal transportation combining truck services and inland waterways (barges) can be found in Inghels et al. (2016), where it is shown that the use of intermodal transportation using barges can help to reduce both costs and emissions and negative externalities.

Trends and future research: As for operational problems, there is a lack of research on intermodal transportation integrated with the sea leg. Recent trends from shipping companies suggest that plans for future further vertical integration are beneficial. Most of the largest shipping companies are already main actors in the container terminal industry, like Tanjung Pelepas APM terminal (APM is the same company holding Maersk), MSC bought, in 2015, the Maasvlakte terminal DDN in Rotterdam and COSCO, with the acquisition of OOCL, entered the Long Beach Container Terminal, one of the terminal with the higher traffic in the world. As indicated in Notteboom et al. (2017), shipping companies define their live services on the basis of their presence in container terminals, preferring to concentrate traffics and transshipment in those ports where they are able to directly supervise loading and unloading operations.
The next step in integration will be to expand into inland intermodal dry ports. With a foreseeable change of the current modal split in favour of rail transportation, service network design problems should focus on considering the optimization of an integrated network that extends outside the boundaries of maritime transportation to consider dry ports. Integrated network design, service network design, cargo routing, fleet deployment and service scheduling can potentially offer better solutions when compared to the currently adopted ones.
Highways of the sea as an alternative to road transportation is still a discussed topic and an interesting field of research (a recent quantitative analysis is presented in Lupi et al. (2017)). More studies on optimizing the service offered by the highways of the sea should be able to foster its growth and increase the use of such an intermodal transportation.

2.5 Air Transportation

Air transportation has recently grown in relevance thanks to e-commerce practices, capable of guaranteeing to customers fast delivery of products from and to the whole globe. To achieve this goal, the transportation of freight through air services is often the only option. Moreover, in the last lustrum, when most of the retail and distribution largest companies (Amazon, Walmart, DHL, UPS, Google are some examples) announced their respective drone delivery projects, a great interest sparked to explore optimized solutions for last mile delivery using drones, technically known in the literature as Unmanned Aerial Vehicles (UAV).

2.5.1 Operational and tactical/strategical problems

Operational problems in recent years mostly focused on exploring optimal solutions and strategies to effectively exploit the use of drones to carry out last mile deliveries. Since its introduction in Murray and Chu (2015), the Flying Sidekick Traveling Salesman Problem (FSTSP) received much attention by researchers. The problem consists in identifying the best path to be followed by trucks and drones, both collaborating to optimally deliver small parcels to customers with the objective of minimizing the delivery time. Developments can be found in Carlsson and Song (2017), where the authors are able to demonstrate that the improvement in efficiency is proportional to the square root of the ratio of the speeds of both truck and UAV. Dell'Amico et al. (2019) present a series of valid inequalities to be used in FSTSP formulations. The traveling salesman problem with drones (TSP-D) also explores the collaboration between trucks and drones to carry out deliveries to final customers with minor differences with respect to FSTSP. Poikonen et al. (2019) introduce a tailored branch and bound algorithm for the TSP-D.
Kitjacharoenchai et al. (2019) and Agatz et al. (2018) propose models where the objective is the minimization of delivery times, while Ha et al. (2018b) and Ha et al. (2018a) explore the same problem but seek the minimization of costs. Routing problems are studied in Wang and Sheu (2019), Poikonen et al. (2017) where the vehicle routing problem with drones (VRPD) is presented. Wang et al. (2017b) analyze various VRPD scenarios and present a worst-case analysis. Pugliese and Guerriero (2017) study the last-mile delivery with time windows problem using drones.
The use of drone stations is studied in Kim and Moon (2018) and Ferrandez et al. (2016).
Apart from UAV deliveries, operational problems in air transportation are scarcely studied. Ruan et al. (2016) optimizes a flow problem for the intermodal transportation of medical supplies. Often, the areas struck by natural calamities are inaccessible with normal means of transportation and, thus, the optimization of the multimodal flow to be served with trucks and helicopters is needed. An interesting overview of humanitarian logistics, often making use of helicopters, has been done

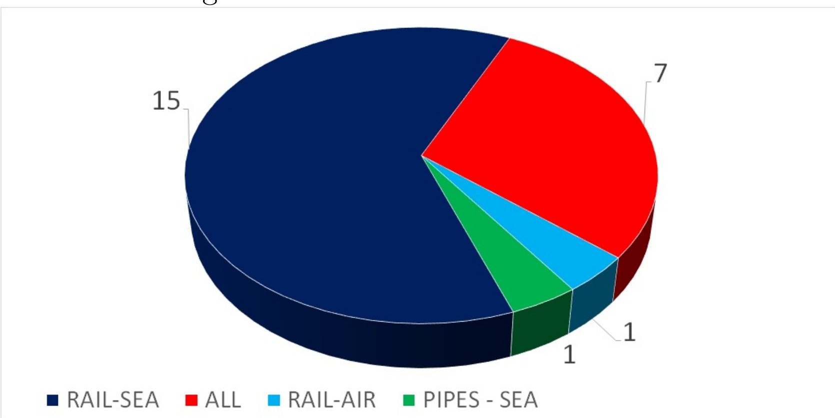
by Ertem et al. (2017). The ATFFSP, introduced to the literature in Archetti and Peirano (2019), is the optimization problem tackled by freight forwarders who need to handle multiple air transportation shipments, as depicted in Chapter 3.
Since the author was unable to identify recent tactical nor strategical problems involving the use of two modalities, one of which is air transportation, the dedicated subsection will not be reported. If we do not consider problems contained in Section 2.6, the only examples of optimization problems involving the use of trucks and aircrafts is in SND problems. An international courier needs to develop a dense network of air services and road pickup/delivery services in order to offer to their customers fast and reliable transportation schedules. Identifying hubs locations and the services connecting hubs and collection/delivery areas is the main focus of SND problems, tackled in Crainic and Rousseau (1986), Barnhart and Schneur (1996), Yang (2009) and Armacost et al. (2004).

Trends and future research: Problems involving a combination of air transportation with either rail or truck have been rarely explored by the literature, apart from SND problems. Mostly, the literature focused on hub optimization problems as in Saberi and Mahmassani (2013), Alibeyg et al. (2018) and Yang et al. (2016), but intermodality is never considered and environmental aspects are rarely addressed. A review of the problems related to air transportation treated by the literature can be found in Ginieis et al. (2012). The use of UAV is the evident trend in intermodal air transportation literature. The studies, though, do not consider real data instances and purely rely on randomly generated scenarios. Recently, Jeong et al. (2019) explored real-world feasible solutions, considering both payload-energy dependency and the activation of no fly zones. However, they applied their model to the randomly generated benchmark instances presented in Murray and Chu (2015) and not to real data. It will be of great interest to study real applications to see if the solution found generates valuable improvements in real life situations. Integration between air and maritime transportation seems unlikely, as both the modalities are used for international, long distance trades and the characteristics of one modality are the opposite of the other (maritime is a slow, low cost transportation while air is an extremely fast and expensive option), making them mutually exclusive most of the times. On the other side, networks integrating rail and air transportation are worth to be studied. Right now, most of the air companies move their goods from hub to hub, if positioned in the same region, mostly by truck services. Creating rail network connecting airports with other airports or collection areas can be a great improvement both in terms of quality of service and environmental impact.

2.6 Multimodal transportation using three or more modalities

In this section are treated the works that consider the planning and management of shipments involving more than two modalities. This is very common, for instance, in international maritime transportation, where the shipment is picked up at shipper's location using a transport unit such as a container. Commodities are loaded in the container and then moved to an intermodal rail-road terminal. The container is moved through a rail service to the maritime port, where it is loaded on a container vessel and the same pattern is symmetrically repeated at the destination country. The goal of obtaining a better modal shift, less dependent on road transportation, increases the potential interest for problems involving multimodal transportation with three or even more modalities used, and generates the need of properly designed intermodal networks and operational systems. Figure 2.1 shows the number of papers studying problems of multimodal transportation with more than two modes, for each combination of modes used.

Figure 2.1: Modalities combinations



Of the studies considered, 6 tackle operational problems, while 10 and 8 studies are focused on optimizing tactical and strategical issues, respectively.

2.6.1 Operational problems

Operational problems in multimodal transportation, with the use of more than two modes, are driven by the need of combining different legs, served by different types of transportation means, in a cost efficient way while at the same time maximizing the service offered to customers. The most common problem is the selection of the transportation modes, focusing on the choice of the different services between those available to move freight from origin to destination throughout a given multimodal network.

Similarly to intermodal rail-road transportation, the structure of transportation networks that make use of multiple modes fits perfectly with flow formulations. Thus, the selection of best routes is often modeled as a multimodal multicommodity flow problem as in Chang (2008), Xiong and Wang (2014) and Tao et al. (2017). A nice theoretical result for multicommodity network flow problems is shown in Gendron and Gouveia (2016). The authors consider the piecewise linear multicommodity network flow problem, with the addition of a constraint specifying that the total flow on each arc must be integer. The formulation is discretized and successively improved through the implementation of valid inequalities. Solutions are identified using Lagrangian relaxation providing high quality lower and upper bounds. Another interesting solution method using Danzig-Wolfe decomposition in a column generation algorithm is presented in Moradi et al. (2015). In Baykasoğlu and Subulan (2016) the authors propose a multi-objective load planning problem with the goal of sustainability, capable of generating solutions tailored for intermodal transportation involving road, rail and sea services. One example of the improvements generated by coordinating services of different modalities can be found in Zhang and Pel (2016). In this paper the authors study a real life scenario, the port of Rotterdam, to make a comparison between the typical intermodal approach and the recently introduced *synchromodal* approach (Tavasszy et al. (2017)). The problem presented is a scheduling problem where, by exploiting the features of synchromodality, the objective is to coordinate services of different modalities in order to effectively allow a smooth switch between them, reduce dead times, offer better services and reduce emissions at the same time. Another scheduling problem involving the coordination of trucks, trains and barges transportation services can be found in Behdani et al. (2014) where the authors tackle the intermodal schedule design problem.

Trends and future research: Operational problems are complex and finding good solution is a difficult task. In practice, they are mostly solved by operators using their work experience. The use of operational research techniques can be a powerful tool in the hands of operators since it can help to find better solutions in faster times. Despite that, operational problems are not well studied, with the literature focused mainly on tactical and strategical problems. Researchers interested in the topic should explore ways to solve operational problems that considers coordinated and combined systems of different modalities. Moreover, integration can be expanded by considering problems related to warehouse management, yard management for intermodal terminals, service scheduling for handling equipment and other logistics problems not strictly related to transportation.

2.6.2 Tactical and strategical problems

The use of multiple modalities needs reliable and efficient networks in order to be effective. Identifying a proper logistic network is the objective of Logistics Network Design (LND) problems. Ghane-Ezabadi and Vergara (2016) propose the integrated intermodal logistic network design where the objective is the identification of terminal locations and the selection of regular routes and transport modes for commodities. The authors make use of composite variable representing complete paths and find state of the art solutions using a decomposition-based search algorithm. Zhang et al. (2017) present a multimodal logistics network design where the demand is characterized by time windows for pick up and delivery, and environmental concerns in the form of Co2 emissions are implemented. The problem is solved with heuristic approaches.

The same objective of LND is shared by intermodal network design problems. Darayi et al. (2019) propose the design of a network composed by rail, road, sea and air services impacting multiple industries in order to minimize the effects of disruptive events. Dulebenets et al. (2016) tackle the network design problem for the transportation of perishable products. They use real world data to test the design of a transportation network that efficiently uses all the available modalities (road, rail, barge, sea and air transportation) in the far east. Zhang et al. (2018b) shows the positive effects of considering the design of a multimodal transportation network, with a focus on emissions and negative externalities. The same authors in Zhang et al. (2018a) study the optimal location for logistics parks in a multimodal regional logistics system. Network design optimization is studied also in Wang and Meng (2017b) and Lam and Gu (2016).

Most of the times, though, the location component of network design is limited since certain modality exchange locations, like maritime ports or airports, cannot be chosen freely. Henceforth, the study of the optimal design of a service network is far more prominent in the literature. Qu et al. (2016) and Liotta et al. (2015) study intermodal SND problems where the modalities used are rail, road and maritime services (both deep and inland water) with a particular attention to environmental aspects, especially regarding emissions and environmental sustainability. The logistics of petroleum and its derivatives is extremely complex and the definition of a logistic network in the downstream section is a widely studied problem. An application of logistic newtwork optimization can be found in Kazemi and Szmerekovsky (2015). Other contribution of SND applied to intermodal transportation with truck,

trains and barges / inland waterways systems are due to Zhang et al. (2015) and Braekers et al. (2013). Demir et al. (2016) propose an environmentally friendly service network design where travel times are uncertain. Their stochastic model is applied to a real case concerning the Danube river.
Intermodal transportation involves a vast number of different kinds of problems like identifying the optimal resource allocation (Wang et al. (2017a)), scheduling problems for carriers (Chen and Schonfeld (2017)), flow optimization problems (Resat and Turkay (2015)) or transportation planning, especially when a synchromodal approach is considered as in Mes and Iacob (2016).

Trends and future works: Strategical and tactical problems are widely studied and the literature is dense of different approaches in both formulations and solution techniques. Interestingly, the majority of the studies analyze the problem without recurring to real data and relying mostly on simulated instances. Randomly generated real life scenarios could potentially miss some key characteristics of real data and therefore it will be of interest the study of the effects of optimization applied to real world instances. Another interesting path to follow is the study of more coordinated systems between the different modalities: different problems, like service scheduling and resource allocation, can potentially influence the network design and the flow of goods within the multimodal network. For instance, intermodal terminal yard management can be improved by integrating both truck, vessels and train schedules in order to improve the efficiency. At the same time, cargo can be redirected to less congested terminals or take different routes if optimization is integrated between modalities.

2.7 Final remarks

Intermodal transportation is an increasingly important topic, of interest for policy makers, transportation operators and shippers. Despite multiple evidences that the use of intermodal transportation is a better option, not only for environmental reasons but also for economical ones, the use of road unimodal transportation is still far too prominent. Environmental aspects are more and more considered in research analysis and this trend should be fostered, awareness on the importance of environmental features in optimization of logistics and transportation is fundamental. For instance, the maritime company CMA-CGM is heavily investing on the renewal of its fleet and predicts to be able to operate 20 new LNG-powered vessels, 9 of them with capacity of 22,000 TEUs. This is a response to the upcoming regulation

IMO 2020, which has the objective to sensibly reduce the amount of sulphur oxide emanated by vessels.
Optimization in intermodality between rail and road is a commonly studied topic and a fertile field for applied researches. Since the aim of a large part of developed countries is changing the current distribution of the modal split, more and more research on exploiting the benefits of intermodality can be applied to concrete real world scenarios. Intermodal studies combining sea transportation with other modalities, on the other side, deserve more attention. Trends in maritime transportation seem to indicate that in the future there will be an increased vertical integration between the sea and land side of multimodal transportation. Already, optimization by maritime companies is affected by their presence at container terminals. A combined, connected and integrated sea-land network, where transportation services are synchronized in order to reduce waiting time for vehicles, idle times at terminal and negative externalities such as pollution, congestion and community severances, is the goal to be achieved in the years to come. Future research should focus on exploring the beneficial effects of optimization of sea transportation fully combined with other modalities in order to foster the vision of a synchronized intermodal transportation.
In order to achieve fully integrated transportation services using different modalities a great deal of changes are due to both organizational processes and technologies. While on one side this is a clear obstacle to the progression of integrated systems, on the other it is an occasion for the development of new organizational patterns and technologies implementing optimization techniques.
Due to its recent spike of interest, it is expected to see an increase of studies focused on optimization of multimodal air transportation. E-commerce and the increasing need to move material from one part of the world to another with limited transit times raised the importance of transportation by means of air mode. Interested researchers should be able to find space for new and interesting studies and applications, especially in strategic and tactical settings that seem to have been ignored so far. To this day, the most prominent area of interest is the use of combined truck and drone transportation in order to carry out last mile deliveries. The field of optimization in drone deliveries is young and hold lot of potential. The authors expect it to be a leading field of research in the upcoming years. The growth of drone research is a perfect example of how any new emerging technology can be an occasion for researchers to develop optimization models never explored before.
Applications of practical scenarios are increasing and this trend needs to be maintained and strengthened. Results in real world instances can be different from theoretical one, thus direct and practical approaches are needed.

Chapter 3

Air intermodal freight transportation: The freight forwarder service problem

Abstract

Despite being one of the most relevant figures in international multimodal transportation, freight forwarding companies optimization problems did not receive much attention from the research community. In this work the goal is to try to fill this gap by presenting the general features of air transportation from the freight forwarder's perspective and to introduce the air transportation freight forwarder service problem (ATFFSP). A MILP formulation of the problem is proposed and tested on real-life data coming from an Italian freight forwarding company. The performance of the model is studied in terms of optimality gap and time needed to reach the optimal solution. Furthermore a comparison between the solution found by the model and the solutions found with the ones provided by the company is carried out in order to evaluate the effectiveness of the model and its ability to find good and practical solutions. Finally, it is studied the possibility of opening a new warehouse facility to better manage services and the corresponding potential benefits are analyzed.

Keywords: Freight forwarder, air transportation, service network, case study, MILP.

3.1 Introduction

International transportation has experienced an enormous growth in the last years thanks to globalization. According to the World Trade Organization, world exports of manufactured goods increased from USD 8 trillion in 2006 to USD 11 trillion in 2016, while world exports of agricultural products increased by an average of 5% per year from 2006 to 2016, as reported in the World Trade Statistical Review 2017. In addition, recent trends in business increased the need to obtain the right goods at the right time, even in cases where goods arrive from far away locations. Also, consumers behavior have been largely influenced by the advent of e-commerce and, in particular, nowadays customers are more and more demanding in terms of speed of service. In this context, air international transport is becoming crucial to satisfy the ever growing requests of fast deliveries. One of the main figures in maritime and air international transport is the freight forwarder. Roughly speaking, freight forwarding companies organize the shipment of goods for their customers (shipper companies), and give operative assistance to ensure that operations run smoothly. As a general rule, door to door international air transportation follows these steps. Goods are loaded at the origin place (usually customer's warehouse) and are then carried to an airport, from where they fly to another airport in the destination country. There, they need to be import customs cleared, and after that they can be delivered to the final destination. In order to be shipped internationally by air transportation, goods must be packed according to air companies regulations (palettized if the number of packages is high, put in crates, forkliftable, ecc.), tags must be put on each package, goods need to be customs cleared and then delivered to air companies at their warehouse (most of the times the warehouse is placed directly at the airport). Usually freight forwarders handle these operations at their own warehouse. This means that loose packages can be loaded at customer's warehouse and properly conditioned once arrived at the freight forwarder's warehouse. After that, they are duely tagged and customs operations are prepared. As soon as the goods are customs cleared, the shipment receives a tracking number, the so-called Movement Reference Number (MRN), which needs to be shown once the shipment is delivered to the air company. Another option is to perform the export customs operations directly at the airport of origin. In fact, most of the airport facilities are equipped to perform them. In order to manage a large number of shipments, freight forwarders need to rely on a large network of logistics partners and shipping agents. The air transportation freight forwarder service problem (ATFFSP) introduced in this chapter consists on selecting the best set of services which minimizes the total costs. In particular, it is considered the problem where a freight forwarder has to organize a set of shipments over a given planning horizon. Multiple options are available either for the choice of the airline service and for the road transportation to and from the airports. The objective is to minimize the total cost to perform all shipments.

The contributions of this chapter of the thesis can be summarized as follows. It is introduced the ATFFSP which, to the best of the author's knowledge, has not been studied before in the literature and, as mentioned before, finds relevant applications. The problem is presented on a time-space network on the basis of which a mathematical formulation is built. It is created a test-bed for computational experiments based on real data coming from the Italian freight forwarding company that inspired this work. The formulation is tested on this test-bed and the results are validated by comparing them with the solutions provided by the company. In addition, the potential benefit of opening a new warehouse facility is evaluated.

The chapter is organized as follows. In Section 3.2 we review the literature on air transportation, network design, service network problems and liner shipping, which is closely related to ATFFSP. Section 3.3 provides the problem description and the modeling through a time-space network. The mathematical formulation is presented in Section 3.4 while Section 3.5 is devoted to computational experiments. Finally, some conclusions are drawn in Section 3.6.

3.2 Literature review

Air transportation of both passengers and commodities presents a multitude of criticalities which offered a fertile ground for research. Barnhart et al. (2003) present a general outline of applications in the air transport industry, surveying problems and case studies divided in three macro-categories: aircraft and crew schedule planning, airline revenue management, applications to aviation infrastructure. A previous work from Etschmaier and Rothstein (1974) already proposed a general view of the impacts that operational research had on airlines, with a special focus on various aspects of their management. Rezaei et al. (2017) study which consolidation policies should be used by airline companies in order to optimize the truck load from collection facilities to hub airports. Three policies are proposed and performance analysis is carried out through the study of KPIs. The best policy varies according to the collection facility structure and characteristics.

Moving to the more general topic of transportation planning, Guastaroba et al. (2016) present an overview of the literature with a particular focus on freight transportation planning with intermediate facilities. Distribution operations make great use of such kind of facilities for different operations as consolidation, transshipment and storage. The authors identify three major branches of study: vehicle routing problems (VRP), transhipment problems (TP) and service network design problems (SNDP). VRPs focus on finding the optimal vehicle routes. In this kind of problems, intermediate facilities usually have the function of consolidation centers and/or transhipment nodes (crossdocks), and are utilized to reduce the transportation cost/travel distance and improve the level of service. SNDPs link two key decisions to be tackled by logistic operators. The first is the definition of the service network and its major characteristics, i.e. selecting the routes, the facilities to be used for stops or transshipments, the frequency of each service and the transportation mode. Once the network is defined, the second key decision is how goods move through the network starting from their origin to their destination, i.e. identify the optimal flow of goods. The TP is an extension of the classical transportation problem where, in addition to origins and destinations, we have an additional set of vertices corresponding to transshipment facilities. The ATFFSP has links with SNDPs, TPs and freight forwarding transportation problems. Thus, the literature on each of these topics is now revised more in detail.

1. *Service network design.* Barnhart and Schneur (1996) propose a model to design a network for express shipment service using column generation techniques to obtain near-optimal solutions. Armacost et al. (2002) study an Express Shipment Service Network Design (ESSND) problem and propose a formulation that uses what they termed *composite variables*. Basically, these variables represent different combinations of aircraft routes which can be followed by shipments, implicitly describing shipment movements. The problem is formulated as a binary linear programming (BLP) model, which gives much stronger lower bounds than the one related to formulations proposed previously. Cohn et al. (2008) present a slightly different network design and flow problem in which the cost assigned to an arc depends not only on the amount of goods shipped through the arc, but also on other arcs. The idea behind this consideration is that by using the same supplier for other shipments, a global reduction of prices can be negotiated.

2. *Freight forwarding transportation.* Krajewska and Kopfer (2009) study how a road freight forwarding company can optimize its distribution plan by deciding which services are handled with owned vehicles and which are assigned to third-party logistics (3PL) companies. The latter category is further divided in three types of external service: paid on tour basis, paid on daily basis and groupage/consolidation services. The authors propose a mathematical model and a tabu search heuristic. Tyan et al. (2003) proposed an Integer Programming model to study the effect of three consolidation policies in order to optimize the distribution plan of a 3PL acting in a global supply chain.

Aguezzoul (2014) presents a literature review on the 3PL selection problem. Since freight forwarder can, and often do, act as 3PL for their customers, an insight on the most valuated criteria is fundamental in order to design a good service offer. Chang (2008) proposes a model to identify the best routes on an international intermodal network, taking into account that for short haul segments usually road/rail transportation are the best choices while for long haul segments maritime or air services are most of the times mandatory, especially for intercontinental shipments. The aim is to minimize both the cost and the transit time. The author proposes a heuristic approach based on relaxation and decomposition. A real and complete supply chain integration between logistics operators and manufacturers is difficult to achieve. Jung et al. (2008) approach the problem by defining a decentralized planning framework in which both the manufacturer and the 3PL provider optimizes their subproblem (production and distribution respectively) using only partial information, and they show that the results obtained are more than satisfying. SteadieSeifi et al. (2014) give a general overview of studies on multimodal freight transportation planning. They classify the studies in strategic, tactical and operational planning problems and divide the papers reviewed in each category by the differences in the models and the solution methods proposed. Cho et al. (2012) approach the problem by designing a dynamic programming algorithm to find optimal intermodal freight flows considering every possible modality (road, rail, air and sea). Pruning rules are used which are based on time and cost, and a case study considering a shipment from Busan to Rotterdam is presented. Part of the SND literature focused on tackling the problem of designing service network schedules while simultaneously considering asset positioning and balancing. In particular Li et al. (2017) propose an heterogeneous assets-based approach in which instead of balancing the number of arcs they balance the number of items traversing them.

3. *Transportation problems with transshipments.* Lim et al. (2005) are the first to propose an extension of the TP by introducing some characteristics derived by cross-docks networks. In particular the authors propose a model based on a network with multiple facilities where a hard time window is associated with each origin and destination. Moreover, transportation services may have a fixed schedule where departure and arrival time cannot be modified (line services like railways, maritime container transportation or airway transportation) or a flexible schedule where departure and arrival can be modified (the typical example is an FTL (full truck load) service). The objective of the problem is to identify the optimal set of shipping schedules which minimizes the total transportation and storage cost. Various scenarios are analyzed and

the authors show that most of them generate $\mathbb{NP}$-hard problems. Mia et al. (2012) studied a variant of the single shipment-single delivery case, where destinations have both soft and hard time windows. Soft time windows represent the favorite time of delivery: if they are not met then a penalty is applied. In case of hard time windows, a higher penalty is associated with a delayed delivery. The objective is to identify the set of service schedules which minimize the total cost given by the sum of transportation, storage and penalty costs. The authors implement two metaheuristics: an adaptive genetic algorithm and an adaptive tabu search. Both of them explore the solution space by exploiting a variable neighborhood search algorithm. Miao et al. (2012) propose a slightly different approach. Time windows are associated with origins and penalties are paid whenever the shipment does not leave the origin within the time window. The authors propose an ILP model inspired by the one in Mia et al. (2012) and design a hybrid genetic algorithm integrating a greedy approach with a variable neighborhood search algorithm. Chen et al. (2006) study a further variant of the problem in a multi-facility network with time windows, both for origins and destinations. The transshipment center has an associated maximum storage capacity as well as a stocking cost. The problem is formulated as an ILP with the objective of minimizing the total cost given by the sum of transportation and storage cost for a given planning horizon. Heuristic approaches are proposed. Ali and Connor (2010) present a study on a two-echelon distribution system. They propose a model and analyze how distribution system characteristics impact on difficulty in solving the model. They also propose a class of valid inequalities called *echelon-flow-based valid inequalities* with the objective of identifying lower bounds for the number of trucks for both the first and the second echelon. A statistical analysis is conducted on the results of the experimental campaign to show how specific model characteristics impact on computational tractability. Snezana and Laporte (2006) analyze the *Pickup and Delivery Problem with Time Windows with Transshipment (PDPTWT)* where goods can be moved from one vehicle to another in transshipment centers. They propose a heuristic and study its behavior on randomly generated instances, while quantifying the economical advantages of transshipment. Jung (2010) considers a problem where requests are to be served by means of an unlimited pool of homogeneous capacitated vehicles. The objective is to minimize the total transportation cost and the author proposes an ant colony optimization (ACO) algorithm. The performance of ACO is then evaluated by comparing its solution with the one found by solving a mathematical formulation of the problem through a commercial solver within a maximum computing time. Results show that the ACO algorithm outperforms the exact solver, in particular for large instances. Lapierre et al. (2004) study a one-to-one transhipment problem. Particular emphasis is put on the calculation of costs, with real-life handling and transportation fares. Each request has an associated weight and density, and fare tables are used to calculate transportation cost from origins to transshipment centers. Transportation between transshipment centers exploits bigger vehicles and allows consolidation of multiple shipments. The authors propose a binary nonlinear programming (BNLP) formulation which seeks the minimization of total transportation costs. A hybrid algorithm is designed combining tabu search and variable neighborhood search and its performance is compared with respect to the solutions found by solving to optimality the mathematical programming formulation of the problem.

In addition to the problems described above, there exist other classes of problems presenting similarities with the ATFFSP, in particular, problems dealing with maritime transportation. More specifically, the ATFFSP shares some common characteristics with the *Liner Shipping Problem*. Liner shipping firms are the main actors in containerized transportation. They move a high number of containers on specialized vessels and they offer a line-based service with fixed schedule, usually with a weekly frequency on each line. Optimization lies in all three decision level. Route selection is a strategic decision since it defines the position of the company on the market. Defining the lines offered requires the knowledge of the demand and the selection of routes and ports to be visited could be heavily constrained by different factors such as existing contracts with terminal operators, alliances between shipping line companies or relationships with other companies. At the tactical level, the main problem tackled by the literature is the liner ship fleet deployment problem (LSFP) which consists in the assignment of different types of vessels to the existing routes (Wang and Meng (2017a)). Lastly, at the operational level, the main problem is cargo allocation both in terms of deciding whether or not to accept a cargo and, eventually, where to allocate it.
The analysis focus mainly on the LSFD and cargo flow problem, since it shares some common properties with the ATFFSP. While the route selection can theoretically and practically be modelled as a VRP (Fagerholt (2004)), most of the contributions in the literature model it as a Service Network Design approach (Wang and Meng (2012), Wang et al. (2014)). Argawal and Ergun (2008) use a time-space network to represent the problem and propose three algorithms: a greedy heuristic, a column generation and a Bender's decomposition based approach. Balakrishnan and Karsten (2017) use an augmented network based on the introduction of arcs representing the so called *sub-paths*, which are the reachable destination nodes for each origin node. Lane et al. (2006) propose a three-step approach: the first step is the

voyage enumeration which identifies the possible routes for a ship, the second step corresponds to the scheduling of the vessel and finally a set partitioning model identifies the best solution. Ting and Tzeng (2003) propose a dynamic programming approach for the same problem while Song et al. (2015) study a multi-objective liner shipping service problem with ports time uncertainty. They propose a genetic algorithm and study the impacts of the various objectives on the structure of the solutions.

The ATFFSP is a service network problem involving the shipment of commodities using the air modality from the perspective of an international freight forwarding company, with the possibility of using intermediate warehouses as consolidation points. In the last years, more and more freight forwarding companies started a progressive process of reduction of fixed assets and began to focus their activity on the organization of shipments and the coordination of the various operators involved, acting more and more as 3PL. To do so, a flexible structure is required and it is obtained by exploiting a wide network of suppliers. The objective is to choose the transportation services to satisfy a set of shipments, minimizing the total cost given by the sum of transportation cost, storage cost and penalties associated with time windows violations.

3.3 Problem description

Freight forwarder's core business is to organize shipments and manage all the operations required to ensure that no delay happens in the transportation, while offering the best service and the most competitive price to customers. The focus is on services that require air international transportation. The problem faced is the one of choosing the best options within the wide offer of transportation services in order to minimize costs and respect delivery times. Freight forwarders usually need to handle different shipments during a certain horizon H composed by T time periods, i.e., $H = (1, \dots, T)$. This means that every shipment needs to be optimized considering the whole set of shipments C. Each shipment $k \in C$ is associated with the following parameters:

- p^k is the place where the shipment origins, it represents the starting point of the shipment where goods are originally available for pick up.
- α^k is the starting time in H at which goods are available for pick up at the origin place p^k.
- d^k is the place where goods have to be delivered to consignee.

- β^k is the time in H by which goods have to be delivered to consignee at delivery place d^k.
- wgt^k is the total weight of the goods of the shipment (expressed in kilograms).
- vol^k is the total volume of the goods of the shipment (expressed in cubic meters).

Once picked up at the origin, the shipment needs to be customs cleared and properly packed and tagged before being introduced at the airport. Such operations can be done in an equipped warehouse or directly at the Airport of Leaving (AoL), if and only if the airport is properly equipped and a shipping agent and a customs declarant are thereby positioned. Usually freight forwarders use their own warehouse to handle such operations if the loading place and the AoL are within reasonable distance, otherwise they rely on a third party supplier. Thus, from the pick up place goods can be delivered to a warehouse or directly to the AoL.
At the AoL, the shipment is loaded on the plane and shipped to the Airport of Destination (AoD). From there, a foreign agent first customs clears and then delivers the goods to the final delivery place.
It is defined the set of locations $L = OR \cup WH \cup AL \cup AD \cup DEST$ where:

- OR is the set of origins, one for each shipment $k \in C$. Thus, $OR = \bigcup_{k \in C} p^k$.
- WH is the set of warehouses (owned or provided by a third party company) that can be used to store shipments for consolidation, perform tagging/packing procedures and export customs clearance.
- AL is the set of AoLs.
- AD is the set of AoDs.
- $DEST$ is the set of delivery locations, one for each shipment $k \in C$. Hence, $DEST = \bigcup_{k \in C} d^k$.

Warehouses and airports usually have a stocking unitary cost st applied on a daily basis.
The goal of the freight forwarder is to determine the best transportation services among those in set S of all possible service options. Set S is defined as $S = TR_{ded} \cup TR_{grou} \cup AC \cup AG$ where:

- TR_{ded} is the set of dedicated truck transportation services, which involve the acquisition of the entire truck for the dedicated transportation from a given origin to a given destination.

- TR_{grou} is the set of groupage/consolidated truck services, i.e., LTL services. Groupage services allow to acquire a certain amount of space available on a truck which follows a fixed schedule based on a line service scheme. These services have prefixed origins and destinations. They may be chosen only in case where origin and destination fit with the requirements of the shipment. In this case, they are generally preferred to dedicated services as they are cheaper.

- AC is the set of air transportation services.

- AG is the set of the agents transportation services in the destination countries. Once the shipment lands at the destination country, it is processed for import customs clearance and then delivered by the shipping agent to the final destination.

Transportation services $w \in S$ are associated with the following parameters:

- p^w is the starting place of the transportation service w.

- d^w is the destination place of the transportation service w.

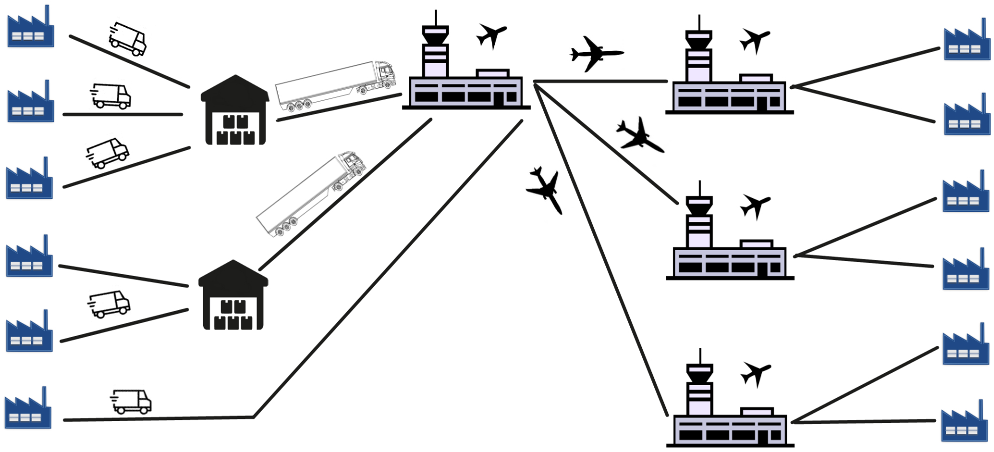
- α^w is the starting time of the service.

- $\tau^w \in \mathbb{Z}^+$ is the service transit time, i.e., the time required to deliver the shipment to the service destination place d^w once it has been picked up at the service starting place p^w. Hence if we consider a generic transportation service w starting at time α^w from p^w, it will arrive at its destination point d^w at time $\alpha^w + \tau^w$.

- γ^w is the service cost associated with transportation service w.

Groupage and air transportation services offer a unitary cost depending on the total weight of the shipment: the higher is the total weight, the lower is the unitary price. Both truckers and air companies divide weight in different ranges. Each range is defined by a lower bound and an upper bound on the weight. If the weight of the goods to be shipped is within the interval limited by the upper and the lower bound, then the associated fare is applied.

Figure 3.1: Network and transportation services



Any shipment k starts from its origin p^k and the delivery at consignee's destination d^k implies that a series of transportation services from the above mentioned list has to be chosen. The possible sequences of transportation services associated with each shipment are depicted in Figure 3.1. They form a layered network where each layer corresponds to a 'segment' of the sequence. We have the following 'segments':

- First, shipments are transported from their origin to a warehouse or an AoL. Both logistic warehouses and AoLs act as hubs in a hub and spoke network and are exploited to consolidate shipments whenever possible. For pick up operations at shipment's origin place, only dedicated transportation are considered, as it is assumed that no groupage service serve the pickup origin (and this is what mostly happens in reality).

- Shipments that are transported to a warehouse have then to be moved to an AoL. As mentioned above, warehouses can be used as a consolidation point and not only to complete customs and tagging/conditioning operations. If possible, different shipments are then collected in a warehouse to be shipped all together to the same AoL using a groupage service. This way, it may be possible to reach a higher weight range and obtain a lower transportation cost. When it is not possible to combine more than one shipment in a groupage transportation service, dedicated transportation is chosen.

- The next step is the air transportation between the AoL and the AoD. Similarly to groupage truck services, it is possible to consolidate different shipments under one airwaybill in order to pay a smaller unitary freight. To do so, not only the couple O/D of airports must be the same for all consolidated shipments, but also the same air company and flight must be chosen.

- Finally, shipments are transported from the AoD to their final destination. Import customs clearance and delivery to door at the destination country are handled by foreign agents. Thus, the freight forwarder who is handling the shipment is not involved in managing service operations once the shipment is taken in charge by the foreign agent.

To formalize the problem it is used a time-space network which is described in Section 3.3.1. Section 3.3.2 is dedicated to the description of how service costs are calculated.

3.3.1 Time-space network

Here is introduced a time-space network $G = (V, A)$, represented in Figure 3.2, with $V = V_{OR} \cup V_{WH} \cup V_{AoL} \cup V_{AoD} \cup V_{DEST}$ where:

- $V_{OR} = OR$: set of nodes associated with origin places of all shipments $k \in C$. We associate a node with every origin $p^k \in OR$.

- $V_{WH} = \{wh_j^t \mid t \in H, j \in WH\}$: set of nodes representing all the warehouses in WH, at every time $t \in H$.

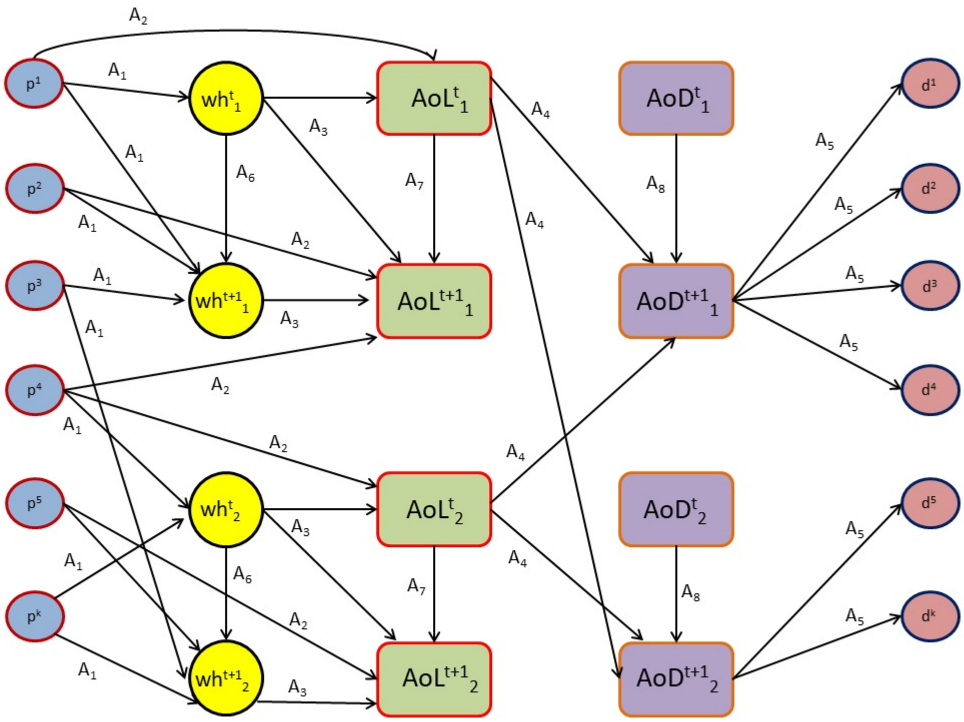
- $V_{AoL} = \{AoL_j^t \mid t \in H,\ j \in AL\}$: set of nodes representing all AoLs in AL at each time period $t \in H$. If properly equipped and a shipping agent is in place, the AoL can be used as warehouse for customs clearance and tagging operations. It is introduced the parameter $M_j = (0, 1),\ j \in AL$, to represent such possibility when it is equal to 1, otherwise it is equal to zero. Nodes $AoL_j^t \in V_{AoL}$ are associated with a value of parameter $M_{AoL_j^t}$ which is equal to the value M_j of the corresponding AoL $j \in AL$.

- $V_{AoD} = \{AoD_j^t \mid t \in H, j \in AD\}$: set of nodes associated with AoDs in AD at each time period $t \in H$.

- $V_{DEST} = DEST$: set of nodes associated with delivery places. We associate a node with every destination d^k.

Note that nodes in V_{OR} and V_{DEST} are not associated with a time period $t \in H$. In the following it is referred to a node of the time-space network as a general node i or j without specifying its set, unless it is necessary to avoid confusion. Arcs are associated with transportation services. Their origin and destination correspond

Figure 3.2: Time-Space Network



to vertices in the sets mentioned above. The set of arcs is then defined as $A = A_1 \cup A_2 \cup A_3 \cup A_4 \cup A_5 \cup A_6 \cup A_7 \cup A_8$ where:

- $A_1 = (i, j)\ \forall\ w \in TR_{ded} \mid i = p^w \wedge i \in V_{OR}, \alpha^w \geq \alpha^k; j = d^w \wedge j \in V_{WH} \mid t = \alpha^w + \tau^w$: Set of arcs representing dedicated transportation services connecting the origin of shipments with a warehouse.

- $A_2 = (i, j)\ \forall\ w \in TR_{ded} \mid i = p^w \wedge i \in V_{OR}, \alpha^w \geq \alpha^k; j = d^w \wedge j \in V_{AoL} \mid t = \alpha^w + \tau^w$: Set of arcs representing dedicated transportation services connecting the origin of shipments with a airport of leaving.

- $A_3 = (i, j)\ \forall\ w \in TR_{ded} \cup TR_{grou} \mid i = p^w \wedge i \in V_{WH} \mid t = \alpha^w; j = d^w \wedge j \in V_{AoL} \mid t = \alpha^w + \tau^w$: Set of arcs connecting warehouses with AoLs. Since warehouses are usually used as consolidation facilities, both dedicated and groupage services are considered.

- $A_4 = (i, j)\ \forall\ w \in AC \mid i = p^w \wedge i \in V_{AoL} \mid t = \alpha^w; j = d^w \wedge j \in V_{AoD} \mid t = \alpha^w + \tau^w$: Set of arcs representing air transportation services, linking AoLs with AoDs.

- $A_5 = (i, j)\ \forall\ w \in AG \mid i = p^w \wedge i \in V_{AoD} \mid t = \alpha^w; j = d^w \wedge j \in V_{DEST}$: Set of arcs representing the last segment of shipments where foreign agents deliver goods from the AoD to the destination.

- $A_6 = (wh_j^t, wh_j^{t+1})\ \forall\ t \in H \mid 1 \leq t \leq T-1; wh_j^t \in V_{WH}$: arcs connecting a warehouse at a certain time t with the same warehouse at time $t+1$, meaning that the shipment remains in the warehouse during period t.

- $A_7 = (AoL_j^t, AoL_j^{t+1})\ \forall\ t \in H \mid 1 \leq t \leq T-1; AoL_j^t \in V_{AoL}$: arcs connecting an AoL at a certain time t with the same AoL at time $t+1$. In this case the shipment remains at the AoL in period t.

- $A_8 = (AoD_j^t, AoD_j^{t+1})\ \forall\ t \in H \mid 1 \leq t \leq T-1; AoD_j^t \in V_{AoD}$: arcs connecting an AoD at a certain time t with the AoD at time $t+1$, meaning the shipment remains in the AoD at time t.

It is to be noted that arcs in sets A_1, A_2, A_3, A_4, A_5 are associated to transportation services, i.e. every arc corresponds to a different service. Services differ in price (γ^w), starting time (α^w) and transit time (τ^w). Due to the difference in transit time, a node in Figure 3.2 belonging to a layer of the network may be linked to different nodes of the following layer which all correspond to the same location which, however, is reached at different times by using different transportation services. Note that nodes related to the same location in different time periods (like wh_1^t and wh_1^{t+1}) represent the possibility of reaching/leaving the location at different points in time. Arcs linking two nodes of this kind represent the fact that the shipment is stored at the location for one period.

3.3.2 Service costs

Before presenting the mathematical model, it is presented an explanation on how service costs γ^w are calculated. For dedicated transport services $w \in TR_{ded}$, the calculation of the price is fairly intuitive, since it usually consists of a unitary costs applied to the distance between the starting point and the destination point. Concerning groupage services, LTL operators offers rates depending on the quantity to be transported. Different rules are used to define the fares. US companies for instance use the National Motor Freight Classification (NMFC) to define a set of 18 classes. Each class is identified by considering four characteristics of the shipment (density, handling, stowability, liability/value). To get the rate applied to the shipment one needs to determine the unitary fare by crossing the proper class and weight on a fare table and then multiply it for the total weight of the cargo. While the logic behind is the same, European LTL operators employ a slightly different approach based on a *weight conversion*. The unitary freight is not applied to the real weight of the shipment, but to the so called *chargeable weight* which

is the higher between the real weigh and the volumetric weight (each cubic meter is converted into kilograms with a certain conversion rate). In this work it will be considered the system applied by European LTL operators, which is also the system applied by air companies. In particular, groupage transportation suppliers usually offer a unitary freight applied every 100.00 kilograms of chargeable weight. A set of weight ranges is defined, $R^w = \{1, 2, \ldots, |R^w|\}$, and a lower bound l_r and an upper bound u_r are associated with each range $r \in R^w$. There also is a unitary cost $FR^{wr}\ \forall\ r \in R^w, w \in TR_{grou}$. The chargeable weight CW^k_{TR} of shipment k is the highest between the real weight of the shipment wgt^k and the volumetric weight $Volwgt^k_{TR} = vol^k * 300, k \in C$, and is calculated as $CW^k_{TR} = max(\frac{wgt^k}{100}; \frac{Volwgt^k_{TR}}{100})$. The unitary cost FR^{wr} is applied if $l_r \leq CW^k_{TR} \leq u_r$. Hence, the cost of a groupage service for a particular shipment is $\gamma^w = FR^{wr} * CW^k_{TR}, w \in TR_{grou}, r \in R^w, k \in C$. Similarly, air companies offer a unitary airfreight which is applied every 1.00 kilogram of chargeable weight. As for the groupage service, there is a price list based on a set of weight ranges $R^w = \{1, 2, \ldots, |R^w|\}$. Each element in R^w is associated with a lower bound l_r, an upper bound u_r, and a unitary airfreight $FR^{wr}\ \forall\ r \in R^w, w \in AC$. The chargeable weight CW^k_{Air} is the highest between the real weight of the shipment wgt^k and the volumetric weight $Volwgt^k_{Air} = vol^k * 167, k \in C$, and is calculated as $CW^k_{Air} = max(wgt^k; Volwgt^k_{Air})$. The airfreight FR^{wr} is selected when $l_r \leq CW^k_{Air} \leq u_r$ and the total cost for an air service is $\gamma^w = FR^{wr} * CW^k_{Air}, w \in AC, r \in R^w, k \in C$. Finally, concerning agents in AG, they are consulted for local charges. So, costs $\gamma^w, w \in AG$, are provided ad-hoc by agents for each shipment. In the following, we define as CW^k the chargeable weight of shipment k and avoid the subscript when this does not generate confusion.
Moreover, it is considered the late arrival penalty θ^+_k as the monetary expression of the damage caused by a late arrival, and θ^-_k the monetary gain (if it exists) for an early arrival. As a general rule, it is assumed that $\theta^+_k >> \theta^-_k$ since usually the economical damage of a late arrival is far greater than the advantage of an early arrival. Lastly, stock costs $st_{(i,j)} \mid (i,j) \in A_6 \cup A_7 \cup A_8$ are a function of both goods weight and stock time.

3.4 Mathematical Formulation

In the following are defined $\tilde{A} = A_1 \cup A_2 \cup A_3 \cup A_4 \cup A_5$ and $\bar{A} = A_6 \cup A_7 \cup A_8$. The mathematical formulation of the problem makes use of the following decision variables:

- $x^{kw}_{(i,j)} = \{0, 1\}\ \forall\ k \in C; (i,j) \in \tilde{A}$ is the binary variable that is equal to 1 if arc (i,j) is used for shipment $k \in C$ with transport service w. Note that the time-space network has one arc for each transportation service w. Thus, the index w on x variables is not needed. It is kept it in the notation for clarity of the formulation.

- $f^k_{(i,j)} = \{0,1\} \ \forall \ k \in C; (i,j) \in \bar{A}$ is the binary variable equal to 1 whenever arc (i,j) is used for shipment k.
- $TT^+_k \in \mathbb{N}$ is the delay of shipment $k \in C$ with respect to β^k.
- $TT^-_k \in \mathbb{N}$ is the anticipation of shipment $k \in C$ with respect to β^k.
- $y^{wr} = \{0,1\}$ is a binary variable equal to 1 if range $r \in R^w$ is applied for service $w \in TR_{grou} \cup AC$.

The objective of the problem is to minimize the total cost, given by the sum of transportation cost, stocking cost and penalty cost:

$$\sum_{k \in C,(i,j) \in \tilde{A}} \gamma^w x^{wk}_{(i,j)} + \sum_{k \in C} \theta^+_k TT^+_k - \sum_{k \in C} \theta^-_k TT^-_k + \sum_{k \in C;(i,j) \in \bar{A}} st_{(i,j)} * wgt^k * f^k_{(i,j)}$$

Dedicated road transportation services and agents services in the destination country are associated with a specific cost for each shipment. Instead, shipment costs γ^w for groupage and air transportation services are defined as the product between the unitary freight FR^{wr} and the chargeable weight CW^k, and are computed as $\gamma^w = \sum_r FR^{wr} y^{wr} CW^k$. Thus, for $(i,j) \in \{A_3 \mid w \in TR_{grou}\} \cup A_4$ the term $\sum_{k \in C} \gamma^w x^{wk}_{(i,j)}$ becomes:

$$\sum_{k \in C;(i,j) \in \{A_3 \mid w \in TR_{grou}\} \cup A_4; r \in R^w} FR^{wr} y^{wr} CW^k x^{wk}_{(i,j)}.$$

This term is non-linear. It is linearized by introducing variables z^{wrk} that substitute the product $y^{wr} x^{wk}_{(i,j)}$. Let us define $\tilde{\tilde{A}} = A_1 \cup A_2 \cup A_5 \cup A_3 \mid w \in TR_{ded}$. The mathematical model becomes:

$$\begin{aligned} \min & \sum_{k \in C;(i,j) \in \tilde{\tilde{A}}} \gamma^w x^{wk}_{(i,j)} + \sum_{k \in C;(i,j) \in \{A_3 \mid w \in TR_{grou}\} \cup A_4; r \in R^w} FR^{wr} CW^k z^{wrk} + \sum_k \theta^+_k TT^+_k \\ & - \sum_k \theta^-_k TT^-_k + \sum_{k \in C;(i,j) \in \bar{A}} st_{(i,j)} * wgt^k * f^k_{(i,j)} \end{aligned} \tag{3.1}$$

$$\sum_{(i,j) \in A_1 \cup A_2 \mid i = p^k} x^{wk}_{(i,j)} = 1 \quad k \in C \tag{3.2}$$

$$\sum_{(i,j) \in A_5 \mid j = d^k} x^{wk}_{(i,j)} = 1 \quad k \in C \tag{3.3}$$

$$\sum_{(i=p^k,j=wh_s^t)\in A_1} x_{(i,j)}^{wk} + f_{(wh_s^{t-1},wh_s^t)}^k - f_{(wh_s^t,wh_s^{t+1})}^k - \sum_{(i=wh_s^t,j)\in A_3} x_{(i,j)}^{wk} = 0 \quad k \in C, wh_s^t \in V_{WH} \tag{3.4}$$

$$\sum_{(i,j=AoL_s^t)\in A_3} x_{(i,j)}^{wk} + \sum_{(i=p^k,j=AoL_s^t)\in A_2} x_{(i,j)}^{wk} + f_{(AoL_s^{t-1},AoL_s^t)}^k - f_{(AoL_s^t,AoL_s^{t+1})}^k - \sum_{(i=AoL_s^t,j)\in A_4} x_{(i,j)}^{wk} = 0 \quad k \in C, AoL_s^t \in V_{AoL} \tag{3.5}$$

$$\sum_{(i,j=AoD_s^t)\in A_4} x_{(i,j)}^{wk} + f_{(AoD_s^{t-1},AoD_s^t)}^k - f_{(AoD_j^s,AoD_s^{t+1})}^k - \sum_{(i=AoD_s^t,j=d^k)\in A_5} x_{(i,j)}^{wk} = 0 \quad k \in C, AoD_s^t \in V_{AoD} \tag{3.6}$$

$$\sum_{(i,j)\in A_5} (\alpha^w + \tau^w) x_{(i,j)}^{wk} - \beta^k \leq -TT_k^- + TT_k^+ \quad k \in C \tag{3.7}$$

$$x_{(i,j)}^{wk} \leq M_j \quad k \in C, (i,j) \in A_2 \tag{3.8}$$

$$\sum_{k\in C} CW^k x_{(i,j)}^{wk} \geq l^r y^{wr} \quad (i,j) \in A_4 \cup \{A_3 \mid w \in TR_{grou}\},\ r \in R^w \tag{3.9}$$

$$\sum_{r\in R^w} y^{wr} = 1 \quad w \in AC \cup TR_{grou} \tag{3.10}$$

$$z^{wrk} \leq x_{(i,j)}^{wk} \quad r \in R^w, w \in AC, k \in C, (i,j) \in A_4 \cup \{A_3 \mid w \in TR_{grou}\} \tag{3.11}$$

$$z^{wrk} \leq y^{wr} \quad r \in R^w, w \in AC \cup TR_{grou}, k \in C \tag{3.12}$$

$$z^{wrk} \geq x_{(i,j)}^{wk} + y^{wr} - 1 \quad r \in R^w, w \in AC, k \in C; (i,j) \in A_4 \cup \{A_3 \mid w \in TR_{grou}\} \tag{3.13}$$

$$x_{(i,j)}^{wk} \in \{0,1\} \quad k \in C, (i,j) \in \tilde{A} \tag{3.14}$$

$$f_{(i,j)}^k \in \{0,1\} \quad k \in C, (i,j) \in \bar{A} \tag{3.15}$$

$$z^{wrk} \in \{0,1\} \quad r \in R^w, k \in C, w \in AC \cup TR_{grou} \tag{3.16}$$

$$y^{wr} \in \{0,1\} \quad r \in R^w w \in AC \cup TR_{grou} \tag{3.17}$$

$$TT_k^+, TT_k^- \in \mathbb{N} \quad k \in C. \tag{3.18}$$

The objective function (3.1) seeks to minimize the total cost which is given by the sum of transportation cost, stocking cost, late arrival penalties minus early arrival benefits. Constraints (3.2) ensure that each shipment is loaded at its origin and delivered to either a warehouse or directly to an AoL, while with constraint (3.3) each shipment is forced to be delivered at its destination. Constraints (3.4), (3.5), (3.6) are the balance constraints for warehouses and airports. Inequalities (3.7) define the variables TT_k^- and TT_k^+. Inequalities (3.8) force variable $x_{(i,j)}^{wk}$ to assume value 0 whenever M_j is equal to zero, i.e. we cannot transfer a shipment from its origin directly to an AoL if it is not possible to handle customs operations at the airport. Constraints (3.9)-(3.10) define variables y^{wr}. As it is assumed that the higher the weight the lower is the unitary price, there is no need to define constraints for upper bounds. Inequalities (3.11)-(3.13) define variable z^{wrk} as product of $x_{(i,j)}^{wk} * y^{wr}$ for both $(i, j) \in A_3, w \in TR_{grou}$ and $(i, j) \in A_4, r \in R^w$. Finally, (3.14)–(3.18) define the domain of the decision variables.

3.5 Computational experiments

In this section the performed computational experiments are presented. In Section 3.5.1, it is described how instances are generated starting from real data. Computational results are presented in Section 3.5.2.

3.5.1 Instance generation

A set of instances for the ATFFSP based on real data are generated as follows. First, a database of 156 shipments is gathered from a North-Italian freight forwarding company. All the shipments considered lie on a two month period and actual goods readiness and delivery times are considered. The length of each time period is set to half a day. This allows us to represent with a reasonable precision the transit time of services without the need to consider too many time periods in H. In the process are considered international shipments for which the origin is in Italy (set OR) and the destination outside Europe (set $DEST$). Set AL is composed by the airports of Milan Malpensa MXP, Venice VCE and Rome Fiumicino FCO, while the airports in AD are reported in Figure 3.3. The set of warehouses WH is composed by a single warehouse, the company's warehouse, located near Bergamo.

For each shipment, we first look at its pick up location in order to determine the necessary dedicated transportation services. For northern Italy locations, dedicated pickups directed to both the airports of Milan Malpensa and Venice (only if the final destination is in the US) and to the company's warehouse are considered. For north-center pickup locations dedicated services for Milan Malpensa, Rome Fiumicino and the company warehouse are created, while for center and south Italy only Rome Fiumicino has been considered. For each shipment a set of 3-4 dedicated transportation services is generated. For dedicated transportation, costs are calculated by considering both quotations received by suppliers and simulated quotations generated by deriving the unitary cost per kilometer from the price list provided by the supplier and then applying it to the distance traveled for the pickup, i.e., start at the supplier headquarter, go to pickup point, go to delivery point and return back to the headquarter. These costs are the ones associated with arcs in A_1 and A_2. Then, connections between company's warehouse and airports in AL, which corresponds to arcs in A_3, can be performed by both dedicated transportation and groupage services. For dedicated transportation are considered three suppliers offering their services twice a day (one in the morning and one in the afternoon), while for groupage there are two suppliers offering transportation services only to Milan Malpensa once a day, in the afternoon. For dedicated services, real quotations received by suppliers are considered, while for groupage services suppliers market fares are applied. By studying the locations of destinations d^k we can list the set of AoDs. Depending on the delivery location, AoDs are chosen according to various parameters as distance from delivery place, number of available airline services offered to that airport, transit time needed to reach it and availability of foreign agents at AoD.

Figure 3.3: Set AD

For each AoL-AoD combination (arcs in A_4), are considered only the air companies which offer a quality level that satisfies the company standard. For every air company, the corresponding weekly schedule is implemented using the published market fares. When available, are also considered the special commercial rates specifically contracted by the freight forwarding company, in order to better reflect the real costs sustained by the company and obtain more reliable results. For delivery services at the destination country (arcs in A_5), real quotations received by foreign agents are considered whenever available, otherwise a realistic simulation of costs is created, in the same way as done for dedicated transportation. Stocking costs applied to arcs in A_6, A_7 and A_8 are calculated as follows. For arcs in A_6, the stocking cost sustained by the company in its warehouse in Bergamo is considered. Concerning arcs in A_7, stocking costs in Milan Malpensa have been calculated as an average of the fares published by the two handling companies operating in the airport. A similar procedure is applied for Rome Fiumicino stocking costs, while for Venice Airport no official stocking costs are available so an estimation based on the charges applied on previous shipments is used. For stocking costs applied in the AoDs (arcs in A_8), the real costs quoted by foreign agents are considered where available. Otherwise, if the destination airport was frequently used in the past, it is calculated an estimation of the unitary costs. If neither of the previous options can be used, an evaluation of the costs aligned to those of the other airports is applied. Regarding the parameters θ_k^+ a θ_k^-, it is used the real monetary values whenever explicitly stated by the shipper or consignee (for instance, shipper could have contractual penalties for each day of delayed delivery, while consignee could have a production downtime due to the late delivery). If these data were not available, they are calculated by considering both goods value and the urgency manifested in the service requests. From the initial database of 156 total shipment are then extracted randomly generated subsets of service requests of different sizes: 10 shipments, 30 shipments, 50 shipments and 100 shipments. For each size ten different instances for a total of 40 instances are created. Table 3.1 shows the number of services for each instance.

The header of the table has the following meaning. TR_{ded}^{or} reports the number of dedicated pick up services, TR_{grou} is the number of groupage transportation services, TR_{ded}^{wh} is the number of dedicated services from the warehouse to AoLs. AC and AG are the number of air services and agent services, respectively.

Table 3.1: Number of services considered for each instance

	$\lvert C\rvert = 10$					$\lvert C\rvert = 30$					$\lvert C\rvert = 50$					$\lvert C\rvert = 100$				
IST	TR^{or}_{ded}	TR_{grou}	TR^{wh}_{ded}	AC	AG	TR^{or}_{ded}	TR_{grou}	TR^{wh}_{ded}	AC	AG	TR^{or}_{ded}	TR_{grou}	TR^{wh}_{ded}	AC	AG	TR^{or}_{ded}	TR_{grou}	TR^{wh}_{ded}	AC	AG
1	124	21	88	1773	526	248	21	176	3913	1906	400	21	176	4767	2788	641	21	176	8107	5266
2	92	21	88	1494	588	268	21	176	3603	1538	384	21	176	5226	2638	633	21	176	7854	5004
3	93	21	88	1427	572	244	21	176	2922	1424	344	21	176	5014	2776	616	21	176	8275	5636
4	65	21	176	1355	484	272	21	176	3922	1790	349	21	176	5706	2582	640	21	176	7805	5268
5	116	21	88	1377	544	256	21	176	3922	1822	352	21	176	5535	2612	585	21	176	7758	5444
6	48	21	88	2285	704	268	21	176	3292	1600	341	21	176	4969	2802	636	21	176	7250	5222
7	124	21	176	1651	616	221	21	176	3740	1584	400	21	176	5573	2980	636	21	176	7792	5634
8	112	21	88	1105	572	220	21	176	3944	1804	372	21	176	4780	2656	608	21	176	7479	5662
9	80	21	88	1501	500	252	21	176	3873	1922	392	21	176	5706	2920	652	21	176	7713	5706
10	108	21	88	1615	528	256	21	176	3756	1864	348	21	176	4815	2584	657	21	176	8010	5414
avg	96	21	106	1558	563	251	21	176	3689	1725	368	21	176	5209	2734	630	21	176	7804	5426
st.dev	24.32	0	35.20	298.39	60.53	17.28	0	0	319.06	164.88	22.84	0	0.00	369.24	134.24	20.54	0	0	279.58	221.85

New setting

The instances described above reflect the current situation of the company's network. Instances related to a setting where an additional warehouse is opened by the company are generated. By analyzing the previous set of shipments, it can be noticed that approximately one shipment out of three has its starting point p^k located in the north-central part of Italy defined by the regions of Tuscany, Emilia-Romagna and the north of Marche/Umbria. Thus, the city of Bologna is chosen as location of the new warehouse, since it is close to this area and it is strongly connected via highways to others areas. The ten instances with size of 50 shipments are edited by adding the warehouse in Bologna in order to study the potential convenience of the new warehouse. Groupage and dedicated services to and from the Bologna's warehouse are generated similarly to the previous set of instances.

3.5.2 Computational results

In Section 3.5.2 the formulation performance with respect to the size of the instances is evaluated. Section 3.5.2 provides a detailed analysis of the performance behavior. The solutions found for each instance are then compared with the service offered by the company in Section 3.5.2. Costs, transit time and services chosen are compared. In Section 3.5.2, it is evaluated the potential benefits of the new warehouse in Bologna.

Performance of the formulation

First, the performance of the problem formulation considering the size of the instances is analyzed. Table 3.2 reports, for each instance, the number of variables (Var), the number of constraints (Con), the solution time in seconds (Time) and the optimality gap (Gap). The model has been implemented in $C\sharp$, 64-bit, on a i3-4005U 1.7 GHz processor, 4 GB DDR3 Ram portable computer. CPLEX 12.5 has been used as MIP solver.

Table 3.2: Model performances

	$\lvert C\rvert = 10$				$\lvert C\rvert = 30$				$\lvert C\rvert = 50$				$\lvert C\rvert = 100$			
I	Var	Con	Time	Gap	Var	Con	Time	Gap	Var	Con	Time	Gap	Var	Con	Time	Gap
1	27,113	45667	3.040	0	101,093	192,334	920.662	0	126,321	234,240	97.752	0	352,706	705,687	213.567	0
2	23,768	40667	5.456	0	79,666	149,111	128.139	0	105,551	184,653	956.211	0	351,010	708,670	307.184	5.14%
3	19,778	32171	2.023	0	44,537	71,309	25.942	0	122,760	224,535	57.749	0	369,968	747,723	306.814	4.90%
4	21,396	36627	1.375	0	81,689	148,043	130.011	0	152,853	291,960	48.310	0	368,337	745,955	319.217	6.22%
5	18,270	28156	1.729	0	91,616	169,614	15.731	0	189,915	379,592	506.171	2.20%	357,420	722,103	308.506	7.32%
6	34,674	60128	3.979	0	61,543	103,430	14.239	0	137,751	259,184	784.539	0	356,275	703,873	308.698	6.04%
7	22,123	36190	1.441	0	71,337	124,684	6.059	0	149,539	285,941	65.615	0	394,838	795,536	207.458	8.27%
8	17,908	29193	2.367	0	106,975	203,901	140.216	0	136,349	258,673	161.196	0	353,082	694,938	306.622	13.13%
9	20,587	33496	1.193	0	94,832	178,500	146.731	0	158,748	306,946	286.216	0	443,663	914,687	182.195	17.51%
10	20,102	31550	1.184	0	77,617	138,973	22.324	0	137,011	263,756	509.120	0	372,276	755,560	211.105	9.71%
avg	22,571.90	37,384.50	2.38	0	81,090.50	147,989.90	155.01	0	141,679.80	268,948.00	347.29	0.44%	371,957.50	749,473.20	262.00	8.69%
st.dev.	5,035.45	9587.32	1.40	0	18,849.02	40,800.59	275.56	0	23,020.18	52,720.37	327.72	0.98%	28,490.44	65,705.23	52.39	4.19%

The first consideration is that the number of variables and constraints increases, on average, almost linearly with respect to $|C|$. However, there is a high variance for instances of the same size. Consider, for example, instance 2 and instance 5 with 50 shipments, where the number of services to be considered is roughly the same. The difference in the number of variables and constraints is due to the fact that instance 2 presents a high number of shipments with the same AoL-AoD combination, while in instance 5 the shipments are more spread out around the world. For a limited number of shipments (10) the model is very fast in finding the optimal solution. The slowest 10-shipment-size instance employs slightly more than 5 seconds to reach the optimal solution. For instances with 30 and 50 shipments, while optimality is reached in almost all cases, the time to solve the model differs remarkably among instances. If we consider instances with 30 shipments, while instance 7 requires only 7 seconds to find its optimal solution, instance 1 reaches optimality in approximately 920 seconds. Clearly, every instance is different from each other for the reason described above, but model size does not seem to be the key reason for this behavior. If a comparison is made between instance 2 and instance 10 it can be noticed that while they have a similar amount of variables and constraints, solution time differs sensibly (128 seconds against 22 seconds). By looking at instance 5, it can be noticed that despite having a bigger size than both instances 2 and 10, it is faster to solve. A similar behavior is observed for instances with 50 shipments. Instances composed of 50 shipments show promising results though. Despite a sensible increase in model size, the solver is capable of finding the optimal solution in almost all the instances generated, and solution time varies from fast to acceptable. Instance 5 runs out of memory after 600 seconds. Instances with 100 shipments are much more difficult to solve. While the time differs sensibly, in almost all instances with 100 shipments CPLEX runs out of memory and is not able to solve the problem. Thus, a time limit of 300 seconds is fixed. Instance 1 is the only one which reaches the optimal solution within the time limit. With the exception of instances 8, 9 and 10, for all other instances the optimality gap is within 10%. In addition, in almost all instances, CPLEX is very fast in finding the best feasible solution while it is slow in closing the optimality gap.

Complexity Analysis

Since the size of the model does not seem to be the main reason for the differences found in the solution time and optimality gap, we need to study the instances more in depth in order to identify what is the main cause of complexity.

One critical issue is that when shipments are highly different from each other in time of availability and destination, the problem becomes similar to a shortest path for each shipment since there is no, or very few, chance to consolidate shipments together. Solving these instances should be very simple. Therefore, it is supposed that the instances that are more difficult to solve present a higher number of shipments that can be consolidated. There are two possible consolidations: the first one is the groupage consolidation, the second one is the airline consolidation. For each instance, we determine the 'consolidation options' as follows. For groupage, shipments with close availability date (a maximum difference of three time units) originating in the same area (shipments are divided between north Italy and south Italy, central Italy counts for both) are considered. For airline, not only the same conditions as for groupage are considered, but it is also checked if the final destination of the shipment is in the same region (this means the shipments will most probably land at the same airport). These two information are used in order to identify a 'consolidation parameter' (CP) calculated as follows:

$$CP = \frac{(CG + CA)}{|C| * 2}$$

where CG is the number of shipments that can be consolidated in groupage services while CA is the number of shipments that can be consolidated on air services. Here are compared the results found with solution time and optimality gap of the instance and calculate the correlation between CG, CA and CP with both optimality gap and solution time. The results are shown in Table 3.3.

Table 3.3: Correlation between solution time / optimality gap and consolidation parameter

	$\lvert C\rvert = 10$					$\lvert C\rvert = 30$					$\lvert C\rvert = 50$					$\lvert C\rvert = 100$				
IST	CG	CA	CP	Time	GAP	CG	CA	CP	Time	GAP	CG	CA	CP	Time	GAP	CG	CA	CP	Time	GAP
1	5	0	0.250	3.04	0.00%	27	7	0.567	920.66	0.00%	33	5	0.380	97.75	0.00%	99	28	0.635	213.57	0.00%
2	9	0	0.450	5.46	0.00%	23	3	0.433	128.14	0.00%	43	11	0.540	956.21	0.00%	98	32	0.650	307.18	5.14%
3	4	0	0.200	2.02	0.00%	23	0	0.383	25.94	0.00%	40	4	0.440	57.75	0.00%	99	31	0.650	306.81	4.90%
4	4	0	0.200	1.38	0.00%	25	3	0.467	130.01	0.00%	31	6	0.370	48.31	0.00%	98	33	0.655	267.87	6.22%
5	5	0	0.250	1.73	0.00%	25	4	0.483	15.73	0.00%	45	8	0.530	506.17	2.20%	98	34	0.660	308.51	7.32%
6	2	2	0.200	3.98	0.00%	19	3	0.367	14.24	0.00%	46	12	0.580	784.54	0.00%	99	33	0.660	308.70	6.04%
7	2	0	0.100	1.44	0.00%	11	0	0.183	6.06	0.00%	29	2	0.310	65.61	0.00%	100	36	0.680	207.46	8.27%
8	8	0	0.400	2.37	0.00%	25	4	0.483	140.22	0.00%	37	5	0.420	161.20	0.00%	99	40	0.695	306.62	13.13%
9	5	0	0.250	1.19	0.00%	20	0	0.333	146.73	0.00%	38	6	0.440	286.22	0.00%	97	42	0.695	182.19	17.51%
10	5	0	0.250	1.18	0.00%	18	2	0.333	22.32	0.00%	41	9	0.500	509.12	0.00%	98	37	0.675	211.11	9.71%
ρ ST	0.413	0.400	0.580			0.488	0.708	0.602			0.792	0.926	0.881			0.146	-0.311	-0.296		
ρ GAP	-	-	-			-	-	-			0.404	0.134	0.324			-0.435	0.986	0.945		

The last two rows in Table 3.3 report the correlation between CG, CA and CP, respectively, with the solution time for the first row, and the optimality gap for the second row. It seems that consolidating the air leg of the shipment have a strong impact on the difficulty of the model. This is reasonable because, usually, the number of possible choices of consolidation is much higher for air services when compared to groupage services. Focusing on the correlation with the solution time, it can be seen that it increases when the size of the instance increases except for the case where $|C| = 100$. This is due to the fact that, in this case, CPLEX quickly runs out of memory. Concerning the correlation with the optimality gap, it can be observed also in this case that it increases with the size of the instances. Moreover, the instances are further analyzed in order to understand what makes the results different even with similar values of CP, CG and CA. If we consider instance 5 with $|C| = 50$ it can be noticed that, despite having lower values of CP, CG an CA, when compared with instances 6 and 2, it is more difficult to solve. We focus our investigation on how the shipments can be consolidated on airline services because it appears they have a higher impact on the performance of the model. While instances 2 and 6 present mostly couples or triplets of shipments that can be combined together, in instance 5 there are five shipments directed to destinations in California, each one approximately at the same distance from both Los Angeles LAX and San Francisco SFO, opening a wide range of consolidation possibilities. Other three shipments produce a triplet directed to the United Arabian Emirates, again offering a wide range of choices of AoD (Dubai DXB, Dubai DWC and Abu Dhabi AUH). Therefore, it appears that, not only the total number of shipments that can be consolidated together, but also the way this consolidation can be carried out have an impact on the model performance.

Analysis of solutions

In this section, the solutions obtained in Section 3.5.2 are analyzed and compared with the solutions provided by the company. In particular, for each shipment, it is checked the output in terms of totals cost, transit time and services activated. Table 3.4 shows an example of how each instance is analyzed.

SC shows the cost of the shipments found by the model in the optimal solution and CC is the cost for the shipments sustained by the company. Δ is the difference in cost and $\Delta\%$ is the percentage difference. STT is the transit time of the solution of the model, while CTT is the transit time of the service offered by the company. ΔTT is the difference in transit time.

An example of one shipment is now presented. Shipment 30 required to transport 550.00 kilograms of goods from Defendente di Cervasca in northern Italy to Benton Harbor, Michigan, US. Goods are ready at period 2. The delivery has to be made within period 20. Company's choice involved a dedicated transportation from the pick up location directly to the airport of Milan Malpensa MXP. From there, the first available flight to Detroit DTW offered by an american company is taken and the total transit time of the shipment is 3 full days (6 periods, as each period is of a half day) with a total costs of €2,200.00. The solution found by the model, however, choose different services. In fact, instead of going directly to the airport, it first goes to the warehouse where the goods are stocked and then delivered to the AoL Milan Malpensa the day after through a groupage service trasporting three other shipments, with a lower unitary cost. Moreover, once in MXP, the goods are loaded on a direct flight of a different company directed to Chicago O'Hare Airport ORD instead of Detroit DTW. While the unitary freight to Chicago with the second company is slightly higher than the one offered by the first one in Detroit, delivery to final destination is less expensive. Total cost for shipment 30 as per model solution is €1,841.64 with a transit time of 7 periods. With only half a day of difference, which is still earlier than the requested shipment time, the cost is 16.29% lower with respect to what the company actually sustained.

Overall, the optimal solutions found by the model tend to use consolidation and groupage services much more intensively than what the company does. While the company treats shipments mostly as single entities, not considering the other shipments generated during the same period of time, the model exploits a wider view to consolidate shipments and make better choices. Company solutions often handle pickup services with dedicated transportation directly to the airport, while most

Table 3.4: Example of the solution analysis for instance 3 when $|C| = 30$

Shipment	SC	CC	Δ	Δ%	STT	CTT	ΔTT
4	2295	2230	65	2.91%	6	10	-4
6	820	1180	-360	-30.51%	8	6	2
8	4086	5680	-1594	-28.06%	11	14	-3
11	659	740	-81	-11.01%	8	9	-1
13	4275	6130	-1855	-30.26%	14	12	2
16	2076	2540	-464	-18.27%	9	13	-4
18	2835	3770	-935	-24.79%	11	10	1
20	2745	3830	-1085	-28.32%	8	10	-2
21	10326	10800	-474	-4.39%	7	11	-4
29	5284	6030	-746	-12.36%	8	10	-2
47	3113	2900	213	7.33%	8	12	-4
49	2092	2580	-488	-18.92%	5	9	-4
50	6450	9280	-2830	-30.50%	7	9	-2
56	918	1015	-97	-9.51%	12	9	3
60	2830	3100	-270	-8.71%	6	8	-2
62	1644	1960	-316	-16.14%	6	7	-1
66	1717	1900	-183	-9.64%	6	8	-2
67	1200	1550	-350	-22.56%	13	6	7
72	1738	1900	-162	-8.53%	8	9	-1
76	1133	1730	-597	-34.48%	7	11	-4
93	2439	2525	-86	-3.42%	8	12	-4
106	15580	21100	-5520	-26.16%	4	6	-2
109	1679	2390	-711	-29.74%	9	14	-5
113	1442	1540	-98	-6.38%	9	12	-3
134	1754	1540	214	13.91%	2	10	-8
136	1720	1890	-170	-8.99%	7	10	-3
137	679	700	-21	-3.06%	14	9	5
139	8926	9065	-140	-1.54%	10	12	-2
141	1681	2415	-734	-30.38%	3	9	-6
145	945	1130	-185	-16.41%	13	9	4

of the solutions found by the model transit through the warehouse first, where consolidation is done with other shipments using a groupage service. Company uses groupage for 12% of the shipments, while the model employs consolidation in groupage services for nearly 57% of the shipments. The highest differences are observed in air services. When shipments are extremely urgent the selection of

viable services is reduced, almost unique, and so the selection made by the model often coincides with the one made by the company. In other cases instead, the selection is deeply different. The tendency of the company operators is to ship to the nearest airport considering the delivery location of the shipment. While this principle is good to minimize the delivery costs of the last leg, it is not the best choice when considering integrated choices. First, usually the nearest airport is a local, secondary airport not directly served with a flight originating in a foreign country. Thus, transit times are larger since transhipment has to be done, usually in a primary international airport. Secondly, consolidation in air services is bound to the final destination, therefore choosing the nearest airport can lead to missed consolidation opportunities. For example, in one instance there are two shipments, one directed to New York and one directed to Andover, MA, performed by the same air company. Both shipments travel on the same flight from Malpensa to J.F. Kennedy where the second shipment takes the connection to Boston (since it is the nearest airport, handled by the air company through a daily truck service). Despite taking the same flight for the first leg (from Milan MXP to New York JFK) they are not considered as consolidated shipments, since their final destination is different (JFK for one shipment and BOS for the other). Moreover, the freight applied by the air company to BOS is higher than the one applied to JFK, since it requires an extra leg to reach the same destination. The solution found by the model consolidates the two shipments together with final destination in New York and handle deliveries from there. Not only it manages to reach a lower airfreight cost, but the cost of delivery to Andover from JFK is lower if compared with the delivery to Andover from Boston plus the air freight applied to reach Boston from New York. Moreover, company operators often book the fastest flight or the first one to leave (80% of the times), while if the model identifies a slower/later flight which generates a lower cost, it prefers to wait and selects a cheaper option. Differences in air service decisions determine the largest savings shown in Table 3.5. On average, solutions present differences in air service selection in 93% of the shipments. Foreign agent services are usually rather standard and freight forwarding companies do not have much control over them, so there are no notable differences for them.
Table 3.5 shows the aggregate results obtained over the 40 instances. It is compared the solution of the model with the one implemented by the company. In Table 3.5 the comparison is based on the evaluation of the solution cost, i.e. cost of the shipment plus the stocking cost, without taking into account the penalties for late arrival and the gainings for early arrival. Table 3.6 instead compare the value of the objective function taking into account also these two terms.

In Table 3.5 MTC is the total cost of the shipments found by the model while CTC is the total cost sustained by the company. Δ is the difference between the two costs

Table 3.5: Comparison of costs

	$\lvert C\rvert = 10$				$\lvert C\rvert = 30$				$\lvert C\rvert = 50$				$\lvert C\rvert = 100$			
IST.	MTC	CTC	Δ	%Δ	MTC	CTC	Δ	%Δ	MTC	CTC	Δ	%Δ	MTC	CTC	Δ	%Δ
1	30,043.96	32,720.00	-2,676.04	-8.18%	101,295.74	119,690.00	-18,394.26	-15.37%	132,946.52	147,670.00	-14,723.48	-9.97%	274,615.29	300,771.00	-26,155.71	-8.70%
2	21,075.03	23,170.00	-2,094.97	-9.04%	68,208.93	76,360.00	-8,151.07	-10.67%	135,990.59	154,340.00	-18,349.41	-11.89%	244,967.02	278,835.00	-33,867.98	-12.15%
3	19,744.55	21,270.00	-1,525.45	-7.17%	95,081.07	115,140.00	-20,058.93	-17.42%	139,649.93	162,725.00	-23,075.07	-14.18%	273,642.57	314,716.00	-41,073.43	-13.05%
4	16,780.03	18,850.00	-2,069.97	-10.98%	59,568.95	70,160.00	-10,591.05	-15.10%	124,632.54	138,565.00	-13,932.46	-10.05%	281,033.86	319,596.00	-38,562.14	-12.07%
5	31,071.53	40,670.00	-9,598.47	-23.60%	76,222.37	85,165.00	-8,942.63	-10.50%	147,247.89	158,460.00	-11,212.11	-7.08%	282,648.82	324,221.00	-41,572.18	-12.82%
6	32,375.21	37,260.00	-4,884.79	-13.11%	65,462.73	76,616.00	-11,153.27	-14.56%	141,144.93	157,225.00	-16,080.07	-10.23%	253,996.64	288,906.00	-34,909.36	-12.08%
7	25,940.79	30,540.00	-4,599.21	-15.06%	87,809.85	96,820.00	-9,010.15	-9.31%	153,921.35	172,565.00	-18,643.65	-10.80%	282,708.35	325,020.00	-42,311.65	-13.02%
8	18,469.10	21,585.00	-3,115.90	-14.44%	88,104.36	97,305.00	-9,200.64	-9.46%	115,708.16	132,825.00	-17,116.84	-12.89%	258,289.11	282,991.00	-24,701.89	-8.73%
9	18,969.40	22,125.00	-3,155.60	-14.26%	63,763.88	69,591.00	-5,827.12	-8.37%	113,611.80	126,100.00	-12,488.20	-9.90%	285,596.00	309,006.00	-23,410.00	-7.58%
10	28,675.49	32,420.00	-3,744.51	-11.55%	96,504.80	109,880.00	-13,375.20	-12.17%	148,637.28	169,225.00	-20,587.72	-12.17%	265,350.04	303,126.00	-37,775.96	-12.46%
Avg	24,314.51	28,061.00	-3,746.49	-12.74%	80,202.27	91,672.70	-11,470.43	-12.29%	135,349.10	151,970.00	-16,620.90	-10.92%	270,284.77	304,718.80	-34,434.03	-11.26%
St.Dev.	5,925.54	7,619.55	2,324.56	4.70%	15,366.96	18,795.20	4,554.16	3.11%	13,721.35	15,444.82	3,684.38	1.97%	13,991.10	16,807.29	7,231.28	2.08%

and %Δ is the percentage difference calculated as $\%\Delta = \frac{\Delta}{CTC}$. A similar notation is used in Table 3.6. The model shows promising results as total costs for every instance is lower than the one actually sustained by the company. Almost every shipment presents a lower cost with a high rate of coherent routings in the sense that the solution found could actually be used by the freight forwarding company.

Table 3.6: Comparison of objective function values

	$\lvert C\rvert = 10$				$\lvert C\rvert = 30$				$\lvert C\rvert = 50$				$\lvert C\rvert = 100$			
IST	OF MODEL	OF COMPANY	Δ	%Δ	OF MODEL	OF COMPANY	Δ	%Δ	OF MODEL	OF COMPANY	Δ	%Δ	OF MODEL	OF COMPANY	Δ	%Δ
1	26,461.68	31,320.00	-4,858.32	-15.51%	94,045.74	114,732.00	-20,686.26	-18.03%	124,310.52	144,537.00	-20,226.48	-13.99%	249,512.29	290,969.00	-41,456.71	-14.25%
2	12,320.03	15,175.00	-2,854.97	-18.81%	63,276.57	74,854.00	-11,577.43	-15.47%	123,650.59	150,947.00	-27,296.41	-18.08%	219,816.02	268,053.00	-48,236.98	-18.00%
3	17,699.55	19,886.00	-2,186.45	-10.99%	88,991.07	114,407.00	-25,415.93	-22.22%	131,938.93	159,054.00	-27,115.07	-17.05%	256,827.57	309,249.00	-52,421.43	-16.95%
4	15,569.03	18,126.00	-2,556.97	-14.11%	53,766.95	67,199.00	-13,432.05	-19.99%	105,278.79	125,220.00	-19,941.21	-15.92%	267,867.86	314,736.00	-46,868.14	-14.89%
5	29,065.53	39,239.00	-10,173.47	-25.93%	63,964.37	75,552.00	-11,587.63	-15.34%	131,713.93	146,747.00	-15,033.07	-10.24%	255,367.21	308,329.00	-52,961.79	-17.18%
6	30,581.21	37,832.00	-7,250.79	-19.17%	60,081.73	78,169.00	-18,087.27	-23.14%	130,393.93	156,594.00	-26,200.07	-16.73%	227,765.64	276,087.00	-48,321.36	-17.50%
7	23,195.79	29,145.00	-5,949.21	-20.41%	76,079.85	92,652.00	-16,572.15	-17.89%	137,012.35	164,360.00	-27,347.65	-16.64%	258,007.35	312,367.00	-54,359.65	-17.40%
8	17,127.10	23,346.00	-6,218.90	-26.64%	74,639.36	89,263.00	-14,623.64	-16.38%	106,058.16	127,804.00	-21,745.84	-17.01%	232,105.11	270,548.00	-38,442.89	-14.21%
9	10,858.40	14,456.00	-3,597.60	-24.89%	58,617.84	68,107.00	-9,489.16	-13.93%	116,142.29	126,778.00	-10,635.71	-8.39%	263,676.00	297,235.00	-33,559.00	-11.29%
10	26,089.49	31,026.00	-4,936.51	-15.91%	91,106.80	109,065.00	-17,958.20	-16.47%	138,866.28	165,312.00	-26,445.72	-16.00%	241,534.04	290,829.00	-49,294.96	-16.95%
Avg.	20,896.78	25,955.10	-5,058.32	-19.24%	72,457.03	88,400.00	-15,942.97	-17.88%	124,536.58	146,735.30	-22,198.72	-15.01%	252,382.92	293,840.20	-41,457.28	-14.23%
St.Dev.	6,714.77	8,576.54	2,337.95	5.02%	13,984.08	17,692.18	4,571.81	2.88%	11,336.74	14,652.08	5,522.29	3.04%	26,188.72	16,669.59	16,599.48	5.59%

In some situations, the model recreated exactly the choice of services implemented by the company at the same costs. While this could seem to be a questionable result since no cost/transit time reduction is gained, it also means that service selection is the same as the one applied by the company's operators making the model output reliable. Analyzing Table 3.6 it can be seen that, taking into account the entire objective function, the gainings from the model are more substantial.
From a practical point of view the model performs very well and its applicability to real problems is wide. In fact, the size on which tests are made and for which the model is able to find an optimal solution is consistent with what required in practice. In particular, the freight forwarding company which provided the data usually plans the shipments with an horizon of 7 to 10 days and the number of shipments in this horizon is usually much lower than 100, the largest size of the instances tested in this chapter.

New setting

In this set of experiments, we took instances with 50 shipments and added a new warehouse in Bologna. Table 3.7 shows the comparison between the original results and the ones related to the new setting.

Table 3.7: Comparison between the current setting and the one with a new warehouse in Bologna

	Var		Con		OF		ST		GAP		Costs		
IST	NORM	BO	NORM	BO	NORM	BO	NORM	BO	NORM	BO	BO	NORM	%Δ
1	126,321	137,361	234,240	252,582	124,311	124,245	98	102	0	0	132,901	132,947	-0.03%
2	105,551	117,341	184,653	203,031	124,187	123,850	956	302	0	1.87%	136,356	135,991	0.27%
3	122,760	134,095	224,535	242,247	132,523	132,372	58	405	0	0	139,958	139,650	0.22%
4	152,853	164,358	291,960	310,350	105,653	105,496	48	69	0	0	124,925	124,633	0.23%
5	189,915	201,521	379,592	397,754	133,490	131,873	506	305	0	2.84%	147,437	147,248	0.13%
6	137,751	149,443	259,184	277,490	130,151	130,388	785	606	0	4.03%	141,139	141,145	0%
7	149,539	161,601	285,941	304,211	139,265	136,900	66	73	0	0	153,809	153,921	-0.07%
8	136,349	147,865	258,673	276,727	107,508	105,880	161	127	0	0	115,530	115,708	-0.15%
9	158,748	170,960	306,946	325,828	116,154	116,078	286	349	0	0	113,548	113,612	-0.06%
10	137,011	149,109	263,756	282,170	140,646	138,815	509	604	0	0.63%	148,586	148,637	-0.03%
Avg.	141,679.80	153,365.40	268,948.00	287,239.00	125,388.72	124,589.82	347.29	294.06	0	0.94%	135,418.93	135,349.10	0.05%
St.Dev.	21,838.86	21,923.04	50,014.93	50,072.41	11,668.92	11,352.81	310.90	193.18	0	1.39%	13,040.64	13,017.22	0.18%

For each column *NORM* indicates the solution of the instance without Bologna's warehouse, while *BO* indicates the solution with Bologna's warehouse. 'V' is the number of variables, 'C' is the number of constraints, 'OF' is the value of the objective function, 'ST' is the time needed to find the solution while 'GAP' is the optimality gap. 'Costs' reports the total cost of the shipments which corresponds to the value of the objective function excluding penalties for late arrivals and gainings for early arrivals. %Δ is the percentage difference between the cost found by the model in the new instance involving the Bologna's warehouse and the cost found by the model in the original instance. Looking at the difference between total cost and objective function value, it can be seen that shipments are often done in advance (as objective function is lower than cost). While the majority of the instances presents a lower total cost and objective function, this reduction does not seems to be sufficient to justify the investment needed to open a new warehouse. This is primarily due to two key factors. The first is that while the north-center of Italy is the origin of many of the shipments, their number is not high enough to motivate the presence of the warehouse. This is especially true if we consider that shipments are ready in different time periods and it is difficult to consolidate them effectively due to the express nature of service requests. Secondly, the original company's warehouse, located near Bergamo, is not that far and it attracts all the shipments originating in the north of Italy. Since the core market area of the company is based in the north of Italy, Milan Malpensa airport is used far more often than

Rome Fiumicino, allowing the company's warehouse to be a very solid choice in most of the cases. Unfortunately the number of shipments originating from south Italy is very low, otherwise a similar analysis could be carried out considering the opening of a warehouse in this area.

3.6 Final Remarks

Despite being one of the most important figures in international exchange of goods, freight forwarders never received much attention from the literature. This chapter try to fill this gap by introducing the air transportation freight forwarder service problem (ATFFSP). The main features of the problem as well as a MILP formulation are presented. A database of 156 shipments is created from real-life data obtained by a freight forwarding company based near the city of Bergamo, in the north of Italy. From this database 40 instances of different sizes are created, from 10 to 100 shipments. These instances are then solved and the solutions are studied both in terms of model performance and quality of the solution. The proposed formulation is very fast in finding the optimal solution when the number of shipment considered is low, while for average size instances (30 and 50 shipments) results vary sensibly. In any case, the model finds almost always the optimal solution and average solution time is absolutely acceptable. When the size of the instance is high (100 shipments) CPLEX runs out of memory unless a time limit is set. When a time limit of 300 seconds is set, the model is fairly fast in reaching low optimality gaps. The list of services activated in order to fulfill each shipments are coherent with the ones used by the company. Also, for every instance solved, the total cost generated by the solution is lower than the one actually sustained by the freight forwarding company. Finally, we studied the effect of the addition of a warehouse situated in Bologna. The results show that the reduction of costs is not sufficient to justify the investment.

Despite showing promising results, the model proposed covers only partially the wide set of problems that freight forwarders must tackle daily. Further possible developments include a deeper analysis of the characteristics of shipments and services. For instance, dedicated transportation services could be further differentiated based on the type of vehicle used (van, trucks, semi-trailer, articulated, tractor trailer etc.) with additional constraints ensuring that weight and dimensions of goods are consistent with the vehicle boundaries. Similarly, air transportation is carried by companies with different kind of aircrafts. Furthermore, cargo companies are specialized on the use of the so called *freight aircrafts*, bigger than standard airplanes and ad-hoc for the transportation of goods. While the space for goods in passengers flights is limited to the lower cargo deck, with maximum height allowed of at most 160 centimeters and limits on lengths and width too, freight aircrafts allow the use of the much bigger upper deck section of the plane. Furthermore, the model does not consider the shipments with specific requirements (controlled temperature, dangerous goods, out of gauge dimensions). Finally, another direction of research is related to an alternative formulation of the model that is less sensible to the size of the data and offers better performances when the number of shipments increases. The study presented in Chapter 4 move in the direction of trying a different approach to improve the solutions for the problem with a high number of shipments.

Chapter 4

A Matheuristic for the Air Transportation Freight Forwarder Service Problem

Abstract

Freight forwarding companies provide transportation services to shipping companies by organizing shipment of freights from origins to destinations. They typically handle long-haul intermodal transportation requiring synchronization among different transportation legs and modes, as well as complex bureaucratic and administrative operations, like customs clearance for international transportation. Because of the complexity of these operations, shipper companies prefer to focus on their core business activities and are more and more relying on third parties to organize their shipments. In this chapter the focus is on freight forwarding where the main transportation mode is air transportation. The problem has been recently introduced in the literature and finds interesting practical applications related to the recent raise in air freight transportation due to fast delivery times requested by e-commerce customers. In this chapter, it is proposed a matheuristic algorithm based on the construction of feasible routes from origins to destinations and on the solution of a set-partitioning formulation. Computational tests are made on the same instances proposed in Chapter 3, which are based on real data. The results show that the matheuristic is capable of offering good solutions for large size instances within reasonable computing times.

Keywords: Freight forwarder, air transportation, service network, matheuristic.

4.1 Introduction

Freight Forwarding companies (FF) handle shipments committed from their customers (shippers) and are in charge of managing all steps and operations needed to transfer goods from origin to destination. Their services typically require to handle long-haul shipments involving intermodal and, often, international transportation. Focusing on intermodal transportation, what typically happens is that the first and last legs are performed by truck (from origin to the first transfer point and from the last transfer point to destination), while the longest intermediate leg is performed by either train or ship or airplane, depending on the availability of the service, on the characteristics (weight, dimensions, material) and on the requested delivery time of the shipment. Supposing that all kinds of transportation modes are available for a given shipment, then the trade-off between speed and cost of service has to be considered. In fact, the ship transportation is the cheapest but, also, the slowest. On the opposite, airplanes provide a fast but expensive service. This is the reason why the air transportation has been restricted to luxury and niche products for decades. However, in the last years, there has been an exponential growth of air freight transportation, which is now becoming more and more common even for non-luxury goods which used to be transported through cheaper modes. This is mainly due to the increase of e-commerce which, in turn, requires drastically reduced delivery times. As a consequence, fast delivery times have pervaded supply chains in different businesses at all levels. When these short delivery times are coupled with the need of sending goods to far-away destinations, then the only choice is air transportation.

This chapter deals with the problem faced by a freight forwarder handling air freight transportation. The problem has been recently introduced in the literature by Archetti and Peirano (2019) as the Air Transportation Freight Forwarder Service Problem (ATFFSP), as depicted in Chapter 3 where it is proposed a mathematical formulation of the problem based on arcs in a time-space network. Tests are made on instances generated from real data. Results show that the formulation solves systematically instances with 50 shipments while it often runs out of memory for instances with 100 shipments. Also, by comparing the results with the solutions proposed by the company providing the data, it is shown that high savings could be achieved by guaranteeing the same level of service to customers. The ATFFSP finds connections with different problems studied in the literature as revised in detail in Chapter 3. In particular, liner shipping (Fagerholt (2004), Wang and Meng

(2012), Wang et al. (2014), Argawal and Ergun (2008)), air transportation problems (Barnhart et al. (2003), Etschmaier and Rothstein (1974), Rezaei et al. (2017)), service network design problems (Armacost et al. (2002), Cohn et al. (2008)), intermodal freight transportation (Krajewska and Kopfer (2009), Chang (2008), SteadieSeifi et al. (2014), Cho et al. (2012), Li et al. (2017), Tyan et al. (2003), Aguezzoul (2014)), and transportation problems with transshipments (Guastaroba et al. (2016)). However, as described in Chapter 3, none of the above-mentioned contributions addresses the problem from the freight forwarding company perspective as done in the ATFFSP.

The aim of this chapter is to to propose a matheuristic algorithm for the ATFFSP capable of handling instances of larger size with respect to the 50 shipments size which are solvable by the formulation proposed in Chapter 3. In particular, it is proposed a matheuristic algorithm which is based on a set-partitioning formulation choosing the best subset of routes among the set of routes passed to the model. This latter set of routes is constructed through a routes construction algorithm where the basic idea is to generate all feasible routes from origin to destination for all shipments. As the number of feasible routes increases exponentially with the number of transportation services and shipments, acceleration techniques and heuristic procedures for restricting the set of routes constructed are proposed. Acceleration techniques are of two kinds. First, dominance rules are proposed, which enable to discard a good portion of feasible but not interesting routes. Second, it is deviced a procedure which allows to shrink the number of services considered by constructing a virtual service which represents the Pareto frontier of all services shrinked. As acceleration techniques are not enough to restrict the number of routes generated to a reasonable level, it is then developed a heuristic construction procedure which is based on a rule of thumb reflecting what done by practitioners. The main idea is to restrict the set of constricted routes to those that are 'more appealing' in the sense that are more likely to be selected in the optimal solution. This set is then passed to the set-partitioning formulation which selects the best one, thus obtaining a matheuristic. It is performed an exhaustive set of experiments on the instances presented in Chapter 3. The study shows the efficiency of the dominance rules and the efficacy of the matheuristic. The results show that even for large instances the matheuristic is capable of finding good solutions in limited computing times.

The chapter is organized as follows. In Section 4.2 the problem is described while Section 4.3 is devoted to the matheuristic. In particular, at first the set-partitioning formulation is presented in Section 4.3.1 and then the routes construction algorithm is introduced in Section 4.4.

Computational results are illustrated in Section 4.5. Finally, some conclusions are drawn in Section 4.6.

4.2 Problem description

International transportation, especially when multimodal transportation is mandatory as in the case of intercontinental transportation, requires the coordination of a high number of different operators. Our focus is on international intermodal freight transportation where the main leg is carried out by means of air transportation. The handling process can be outlined as follows. Goods are loaded at the starting location of the shipment (typically shipper's warehouse) and from there they are transported either to a warehouse or directly to an airport. Before being delivered to the airline company, goods need to be properly packed according to company's regulations. Moreover goods have to travel with their documentation and packages must be tagged properly. Tagging operations can be done at the selected airport if offices and warehouses are available, otherwise goods need to be transported to an equipped location before being moved to the said airport. In addition, the shipment needs to be customs cleared for exportation. Usually customs declarants base their offices near airports, so this operation can often be done directly there. Otherwise, goods have to first be moved to a customs warehouse. Once at the airport, goods are taken by an airline company which loads them on an aircraft and fly to another airport. With the exception of air companies offering chartering services, where the whole aircraft is entirely chartered for the purpose of the shipment, air companies offer services based on fixed schedules. Once landed at the airport of destination, goods are taken in charge by the local agent who customs clears them and manage the delivery to destination.

To ease the readability of the reader, it is now given a more precise description of the different operations, which are the same as the one described in Chapter 3. Once picked up at the origin location, the shipment can be either transported to a freight forwarder warehouse or directly at an Airport of Leaving (AoL) via dedicated transportation. The latter case is practicable only if the AoL is equipped for customs clearance, otherwise the shipment needs to pass through a freight forwarder warehouse. The transportation from the origin location to an AoL, usually the nearest international airport to the origin area, either direct or through a warehouse, is performed by truck by either a dedicated service or by a groupage service, where different shipments are consolidated. In particular, groupage services are Less than Truck Load (LTL) services which allow to acquire a certain amount of space on a truck which follows a fixed schedule based on a liner service scheme. These services have prefixed origins and destinations. They may be chosen only in case where origin and destination fit with the requirements of the shipment. For this reason, groupage services can be used only for transportation from a freight forwarder warehouse to an AoL. Since usually origin locations and availability time

are sparse, it is assumed that no consolidation is possible at shipment origins and thus we rely on dedicated pickup only. When available, groupage services are prefered to dedicated services as they are cheaper. On AoL, the shipment is loaded on the plane and shipped to the Airport of Destination (AoD). Theoretically, any AoD can be considered. From an operational point of view though, only AoDs in the same country of the destination of the shipment are considered, both for geographical (i.e. usually the nearest airport is in the destination country) and customs reason (i.e. in order to avoid two customs import operation). From there, a foreign agent first customs clears and then delivers the goods to the final delivery place. If the shipment is delivered earlier than the requested time, an incentive can be recognized, otherwise a penalty for late deliveries is applied.
The ATFFSP is the problem of determining the transportation services to send a set K of shipments from origins to destinations over a given time horizon. The time is assumed to be discretized in T time periods. Time periods are considerd having length of half a day. Different options are available to transport each shipment and the objective is to minimize the total cost over all shipments. The transportation requests and services define a network composed by the following set of locations:

- O: set of origins over all shipments $k \in K$.
- H: set of warehouses.
- AL: set of AoLs.
- AD: set of AoDs.
- D: set of destinations over all shipments $k \in K$.

Each shipment $k \in K$ is associated with a set of parameters:

- $o_k \in O$ is the origin location of shipment k.
- $d_k \in D$ is the destination location of shipment k.
- e_k is the earliest time at which shipment k is ready for pickup. Basically, shipment k cannot leave its origin place o_k before time e_k.
- l_k is the latest time of delivery at location d_k as per customer request.
- θ_k^- is the monetary expression of the unitary gain for an early delivery of shipment k.

- θ_k^+ is the monetary expression of the unitary penalty applied for a late delivery of shipment k, where $\theta_k^+ >> \theta_k^-$ as the damage for a late delivery is typically much higher than the gaining from an early delivery.

- w_k is the total weight of shipment k.

Similarly to shipments $k \in K$, each service $s \in S$ is associated with a set of parameters:

- o_s is the starting location of service s.

- d_s is the ending location of service s.

- e_s is the starting time of service s.

- t_s is the transit time of service s, i.e., the time required to travel from o_s to d_s. Therefore, service s reaches its destination at time $e_s + t_s$.

The set of transportation services S is composed by all services available for transporting goods from origins to destinations:

- TR_{ded}: dedicated truck transportation services. They are further divided in:
  - TR_{ded}^{O-AL}: dedicated truck services from origins to AoLs. For each $s \in TR_{ded}^{O-AL}$, we have $o_s \in O$ and $d_s \in AL$.
  - TR_{ded}^{O-H}: dedicated truck services from origins to warehouses. For each $s \in TR_{ded}^{O-H}$, we have $o_s \in O$ and $d_s \in H$.
  - TR_{ded}^{H-AL}: dedicated truck services from warehouses to AoLs. For each $s \in TR_{ded}^{H-AL}$, we have $o_s \in H$ and $d_s \in AL$.

- TR_{gr}: truck groupage services from warehouse to AoL. For each $s \in TR_{gr}$, we have $o_s \in H$ and $d_s \in AL$.

- AC: air company transportation services. For each $s \in AC$, we have $o_s \in AL$ and $d_s \in AD$.

- FA: foreign agents transportation services in the destination countries. For each $s \in FA$, we have $o_s \in AD$ and $d_s \in D$.

The total cost of transporting all shipments from origins to destinations is composed by the following terms:

1. *Transportation cost.* In case of dedicated transportation services $s \in TR_{ded}$, cost is determined by a unitary freight applied to the distance between the starting and ending location for service s. For transportation services $s \in FA$, their cost is simply a fare applied by the foreign agent. Instead, for the case of groupage services and airline services, the cost calculation is more complex. In fact, the unitary cost is a function of the total weigth, stepwise decreasing as the transported quantity increases. In particular, for these services, we have a set of weight ranges $R = \{1, 2, \ldots, |R|\}$, and each range $r \in R$ is associated with a lower bound l_r, an upper bound u_r and a unitary cost, different for each service, f_{sr}.

2. *Stock holding costs.* A daily stocking unitary cost st_i, is paid whenever goods are stocked at warehouses or airports, i.e. $i \in H \cup AL \cup AD$. The unitary cost is applied for every kilogram and depends on the location.

3. *Penalty (gain) for late (early) delivery.* Daily penalty (gain) $\theta_k^+(\theta_k^-)$ are paid for late (early) arrival of shipment k.

The goal of the ATFFSP is to determine the set of transportation services to send all shipments from origins to destinations at the minimum total cost.

4.3 A matheuristic algorithm

In this section it is presented the heuristic algorithm devised for the solution of the ATFFSP. It is based on a routes construction algorithm, constructing a set of feasible routes from origins to destinations for all shipments, and a set-partitioning formulation, choosing the best routes among those generated by the routes construction algorithm.
In the following, it is first presented the set-partitioning formulation (Section 4.3.1) and then the routes construction algorithm (Section 4.4).

4.3.1 Set-partitioning formulation for the ATFFSP

The set-partitioning formulation is based on defining a set of feasible routes Ω_k, for each shipment $k \in K$. Each route $\omega \in \Omega_k$ is defined by the subset of services $s \in S$ used for transporting shipment k from its origin o_k to its destination d_k. For the sake of readability, in the following $\bar{A} = TR_{gr} \cup AC$ is defined. The cost

c_ω of route $\omega \in \Omega_k$ is defined as the sum of transportation cost, holding cost related to stocking goods at warehouses and airports and penalty costs for late or early delivery. Concerning transportation cost, c_ω takes into account the cost of all services except the ones in $\bar{A}$ for which consolidation with goods transported in other routes has to be considered to properly determine the cost. More details on the calculation of c_ω are provided in Section 4.4.1.

The set-partitioning formulation makes use of the following variables:

- $x_{k\omega} \in \{0,1\} \ \forall \ k \in K, \omega \in \Omega_k$: binary variable which assumes value 1 if the route ω is chosen to deliver shipment k.
- $y_{sr} \in \{0,1\} \ \forall \ r \in R, s \in \bar{A}$: binary variable determining whether weight range r is used for service s.
- $z_{srk} \in \{0,1\} \ \forall \ k \in K, s \in \bar{A}, r \in R$: binary variable which determines whether service s with weight range r is used to deliver shipment k.

The formulation is the following:

$$\min \sum_{k \in K} \sum_{\omega \in \Omega_k} c_\omega x_{k\omega} + \sum_{k \in K, s \in \bar{A}, r \in R} w_k f_{sr} z_{srk} \tag{4.1a}$$

$$\sum_{\omega \in \Omega_k} x_{k\omega} = 1 \ \forall \ k \in K \tag{4.1b}$$

$$\sum_{k \in K, \omega \in \Omega_k} w_k x_{k\omega} \geq l_r y_{sr} \ \forall \ s \in \bar{A}, r \in R \tag{4.1c}$$

$$\sum_{r \in R} y_{sr} = 1 \ \forall \ s \in \bar{A} \tag{4.1d}$$

$$z_{srk} \geq y_{sr} + \sum_{\omega \in \Omega_k | s \in \omega} x_{k\omega} - 1 \ \forall \ k \in K, s \in \bar{A}, r \in R \tag{4.1e}$$

$$x_{k\omega} \in \{0,1\} \ \forall \ k \in K, \omega \in \Omega_k \tag{4.1f}$$

$$y_{sr} \in \{0,1\} \ \forall \ r \in R, s \in \bar{A} \tag{4.1g}$$

$$z_{srk} \in \{0,1\} \ \forall \ k \in K, s \in \bar{A}, r \in R. \tag{4.1h}$$

The objective function seeks the minimization of the total cost related to the routes chosen plus the service cost from groupage and airline transportation services. Constraints (4.1b) ensure that for each shipment exactly one route is selected. Constraints (4.1c) determine the weight range for groupage services and air services. Note that, as the unitary transportation cost is decreasing for increasing ranges, only lower bounds constraints need to be applied to determine the correct range. (4.1d) ensure that only one fare range is applied to any groupage or air service. Constraint (4.1e) define variable z_{srk} as the product between variables $x_{k\omega}$ and variables

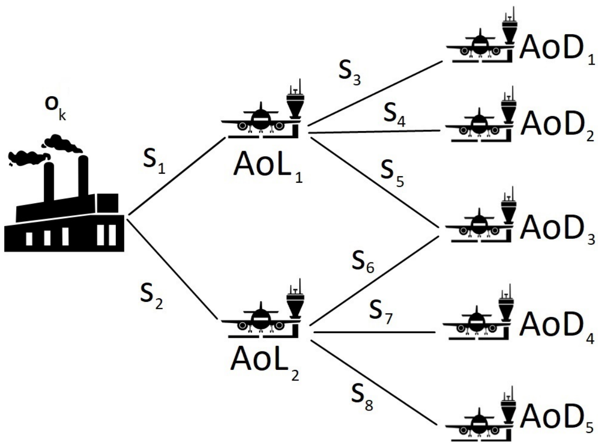
y_{sr}. Constraints (4.1f)–(4.1h) define the domain of the variables. In the following section it is described how the sets $\Omega_k, k \in K$, are constructed.

4.4 Routes construction algorithm

The routes construction algorithm works as follows. First, a procedure which builds the set of all feasible routes from origin to destination for each shipment is devised. As the number of routes constructed might be prohibitively large, techniques to reduce it are presented in Sections 4.4.2 and 4.4.3. Finally, heuristic rules to further reduce the set of routes constructed are presented in Section 4.4.4. First, the construction procedure is presented.

For each shipment k, the set Ω_k contains feasible routes from shipment's origin o_k to its destination d_k. In turn, a route is defined by a sequence of transportation services. In the following it is defined as 'path' a partial route, i.e., a route starting at the origin of a shipment but not yet reaching its destination. It is now defined the concept of 'feasible route' by introducing the concept of *consecutive services*. A service $s' \in S$ is in the set of consecutive services of service $s \in S$ if $d_s = o_{s'}$ and $e_s + t_s \leq e_{s'}$. In this case we say that $s' \in CS(s)$. Moreover, is is also defined the concept of previous service. A service $s' \in S$ is in the set of previous services of service $s \in S$, $PS(s)$, if $s \in CS(s')$. An example is depicted in Figure 4.1.

Figure 4.1: Consecutive services



The service parameters are the following:

- $s_1 \rightarrow o_{s_1} = o_k; d_{s_1} = AoL_1; e_{s_1} = e_k = 1; t_{s_1} = 2.$
- $s_2 \rightarrow o_{s_2} = o_k; d_{s_2} = AoL_2; e_{s_2} = e_k = 1; t_{s_2} = 3.$

- $s_3 \to o_{s_3} = AoL_1; d_{s_3} = AoD_1; e_{s_3} = 3; t_{s_3} = 2.$
- $s_4 \to o_{s_4} = AoL_1; d_{s_4} = AoD_2; e_{s_4} = 2; t_{s_4} = 3.$
- $s_5 \to o_{s_5} = AoL_1; d_{s_5} = AoD_3; e_{s_5} = 4; t_{s_5} = 2.$
- $s_6 \to o_{s_6} = AoL_2; d_{s_6} = AoD_3; e_{s_6} = 4; t_{s_6} = 2.$
- $s_7 \to o_{s_7} = AoL_2; d_{s_7} = AoD_4; e_{s_7} = 2; t_{s_7} = 2.$
- $s_8 \to o_{s_8} = AoL_2; d_{s_8} = AoD_5; e_{s_8} = 3; t_{s_8} = 3.$

If s_1 is chosen, then the shipment is picked up at its origin at time 1 and moved to AoL_1 arriving at time 3. Thus, service s_2, s_6, s_7, s_8 cannot be used after service s_1 since the shipment is in a location which is different from their starting location. Moreover, service s_4 cannot be used too, since its starting time is earlier than the arrival of the shipment at AoL_1. This means that the only consecutive services are s_3 and s_5.
For the sake of readability, it is reminded that the sequence of transportation service is as follows. Once a shipment is picked up, it can be transported directly to the AoL or to a warehouse, from where it will then be transported to an AoL. Then, an air transportation service is chosen to transport the shipment from the AoL to an AoD. Finally, a service offered by a foreign agent at the AoD is chosen to dispatch the shipment to destination. Thus, the sequence of locations visited in a route for shipment $k \in K$ can be of the following two kinds:

1. $o_k \to AoL \in AL \to AoD \in AD \to d_k$.
2. $o_k \to h \in H \to AoL \in AL \to AoD \in AD \to d_k$.

The set Ω_k of feasible routes is defined as the union of all the direct route PD_k of type 1 and the routes that pass through a warehouse PWH_k of type 2. PD_k is defined by the routes involving the choice of the following services:

$$PD_k = \{(s, s', s'') \in TR \times AC \times FA \mid o_s = o_k, e_k \leq e_s, s' \in CS(s), s'' \in CS(s'),$$
$$d_{s''} = d_k, e_{s'} + t_{s'} \leq l_k + \eta, e_{s''} + t_{s''} \leq l_k + \beta\}$$

where η and β are parameters whose meaning is the following. Since the driving logic of air transportation is to reduce as much as possible the transit times required to transport goods, a limit is imposed on the starting times for both air transportation

and foreign delivery services. This limit is calculated by considering the requested delivery time for the shipment and then adding η for air services and β for foreign delivery services. This way we do not consider every existing successive service but only a restricted subset, thus limiting the number of generated routes.
PWH_k is instead defined by the routes involving the choice of the following services:

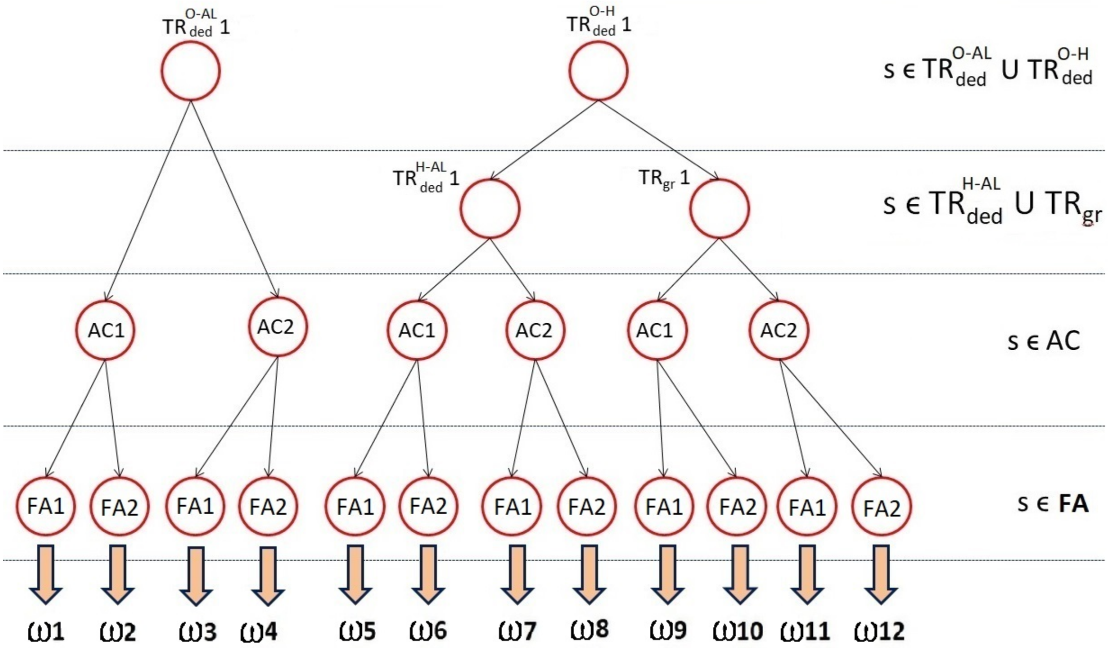
$$PHW_k = \{(s, s', s'', s''') \in TR_{ded}^{O-H} \times TR_{gr} \cup TR_{ded}^{H-AL} \times AC \times FA \mid o_s = o_k; e_k \leq e_s,$$

$$s' \in CS(s), s'' \in CS(s'), s''' \in CS(s''), d_{s'''} = d_k, e_{s''} + t_{s''} \leq l_k + \eta, e_{s'''} + t_{s'''} \leq l_k + \beta\}$$

Given the observations above, for each shipment $k \in K$, the set Ω_k is generated by sequentially inserting consecutive services into paths up to reaching the destination d_k. First, all $AoL \in AL$ and all $h \in H$ belonging to the same country as o_k are considered. Then, the first leg of routes $\omega \in PD_k$ is generated by considering all services $s \in TR_{ded}^{O-AL}$ for which $o_s = o_k$ and $e_s \geq e_k$. Similarly, the first leg of routes $t \in PWH_k$ is generated by considering all services $s \in TR_{ded}^{O-H}$ for which $o_s = o_k$ and $e_s \geq e_k$ and a second leg is added by considering all services $s' \in CS(s) \cup (TR_{ded}^{H-AL} \cup TR_{gr})$. For each path generated this way, the leg corresponding to the air transportation service is added. The number of air transportation services considered is reduced by imposing that they land in the same country as d_k and at least within η days after the expected delivery l_k. Ideally, the shipment should land before the expected delivery since the shipment needs to be customs cleared and delivered, which typically takes a couple of days. Sometimes it is more convenient, or it is just the only possible solution, to land after the required deliver time. However this late arrival should be limited to avoid further delay in the final delivery. Thus, we impose this requirement which reflects company's practice. Finally, a service $s \in FA$ is added to each generated path. An example of the routes construction procedure is depicted in Figure 4.2.

In the example shown in Figure 4.2, Ω_k contains 12 routes of which 4 belong to PD_k and 8 to PWH_k. It is now described, in Section 4.4.1, how the cost of a route c_ω is calculated. Then, in Sections 4.4.2 and 4.4.3, acceleration techniques used to discard routes that are dominated by other routes (Section 4.4.2) and to reduce the number of services considered in TR_{gr} and AC (Section 4.4.3) are presented. They are called 'acceleration' techniques as their aim is to reduce the number of routes generated in order to speed-up the solution of the set-partitioning formulation. Finally, in Section 4.4.4, heuristic rules used to select a subset of potentially most promising routes are presented. Note that, while the techniques proposed in Sections 4.4.2 and 4.4.3 does not discard any potentially optimal solution, the rules defined in

Figure 4.2: Tour Generation



Section 4.4.4 makes a heuristic selection of routes and, thus, they might discard optimal routes.

4.4.1 Route cost

It is now provided the formula to calculate the cost c_ω of route ω. Remember that, as mentioned in Section 4.3.1, this cost does not include the cost for groupage or airline transportation services. Parameter c_s is the cost for services $s \in TR_{ded} \cup FA$ as described in Section 4.2. $\tilde{A} = TR^{O-AL}_{ded} \cup TR^{O-H}_{ded} \cup TR^{H-AL}_{ded} \cup FA$ is defined. The cost c_ω of a feasible route $\omega \in \Omega_k$ is computed as:

$$c_\omega = \sum_{s \in \omega | s \in \tilde{A}} c_s + \sum_{s \in \omega \ | \ o_s \in H \cup AL \cup AD} st_{o_s} \cdot w_k \cdot (e_{s^+} - (e_s + t_s)) + \Delta TT^{sk}$$

where $\Delta TT^{sk} = \begin{cases} ((e_s + t_s) - l_k) \cdot \theta^+ \ when \ ((e_s + t_s) - l_k) \geq 0, s \in FA \mid d_s = d_k \\ ((e_s + t_s) - l_k) \cdot \theta^- \ when \ ((e_s + t_s) - l_k) < 0, s \in FA \mid d_s = d_k \end{cases}$
And it represents the total monetary representation of the penalty (incentive) given to a late (early) delivery.

4.4.2 Dominance rules

A set of dominance rules that are used to reduce the number of routes generated is now defined. Are identified three sets of dominance rules, based on the time at which they are applied in the construction procedure described above. The first set is applied to services before starting the route generation procedure. The second set is applied to paths under construction. The last set of dominances is applied to complete routes.
The first set is composed by the following two rules:

- **Cost dominance:** Consider two services s_1, s_2 where the following conditions are valid: $e_{s_1} = e_{s_2} \wedge t_{s_1} = t_{s_2} \wedge o_{s_1} = o_{s_2} \wedge d_{s_1} = d_{s_2}$, i.e. the services have identical starting place, destination place, starting and transit time. For services $s_1, s_2 \in TR_{ded}^{O-AL} \cup TR_{ded}^{O-H} \cup TR_{ded}^{H-AL} \cup FA$ if $c_{s_1} < c_{s_2}$ then s_1 dominates s_2. For $s_1, s_2 \in AC \cup TR_{gr}$ if $f_{s_1 r} < f_{s_2 r}$ $\forall r \in R$ then s_1 dominates s_2. Clearly, between two services with identical characteristics where one is less expensive than the other, the cheaper one is always preferable. This dominance rule is fairly intuitive but the requirements are very restrictive.

- **Faster Delivery dominance:** Consider two services $s_1, s_2 \in FA$. If $e_{s_1} = e_{s_2} \wedge c_{s_1} \leq c_{s_2} \wedge t_{s_1} < t_{s_2} \wedge o_{s_1} = o_{s_2} \wedge d_{s_1} = d_{s_2}$ then service s_1 dominates service s_2. Between two services in FA with the same starting time, if the cost of the one delivering earlier is the same or even lower than the cost of the other service, then the first service is always preferable. Note that this may not be the case for services in $TR_{ded}^{O-AL} \cup TR_{ded}^{O-H} \cup TR_{ded}^{H-AL}$ as an early delivery may imply a higher stock holding at destination. On the other side for FA services there is no stocking costs upon delivery at destination and, due to how parameters θ_k^- and θ_k^+ works, it is always preferable to have an earlier delivery since it reduces the penalty/increase the incentive.

The second set of dominance rules is applied to paths under construction. It is composed by one rule only which is the following:

- **Waiting dominance:** consider a path p and let s be the last service inserted in p. Let $s_1, s_2 \in CS(s)$ and denote p_1 as the path containing s_1 and p_2 as the path containing s_2. If $o_{s_1} = o_{s_2} 1 \wedge \ d_{s1} = d_{s_2} \ \wedge \ e_{s_1} > e_{s_2} \ \wedge \ e_{s_1} + t_{s_1} = e_{s_2} + t_{s_2} \ \wedge \ c_{s_1} + st_{o_{s1}} \cdot (e_{s_1} - e_s + t_s) \cdot w_k < c_{s_2} + st_{o_{s2}} \cdot (e_{s_2} - e_s + t_s) \cdot w_k$ where $s_1, s_2 \in TR_{ded}^{H-AL} \cup FA$, then path p_1 dominates path p_2. Provided that both the services arrives at the same time, if the stocking costs at the warehouse /AoL generated by delaying the shipment of the goods is lower than the cost difference, then it is worth to wait and path p_1 dominates path p_2. We have this dominance only for services in $TR_{ded}^{H-AL} \cup FA$ since these services starts from a location generating stocking costs ($d_s \in H \cup AD$). Theoretically speaking this dominance can also be applied to services in $AC \cup TR_{gr}$, but since consolidation is difficult to consider a priori and the cost depend on the weight of the shipment multiplied for the activated unitary freight (based on the weight of all the shipments using the same service), it is impossible to compute accurately the total cost of the service and discard certain paths.

Finally, the last set contains two dominance rules that are applied to entire routes. For the ease of exposition, in the following, given a service s in a feasible route ω for a shipment k, s^- and s^+ will be used to denote the services on the same route in $PS(s)$ and $CS(s)$, respectively.
Let us consider two routes, ω_1 and ω_2, differing specifically in a particular leg, i.e., the two routes use exactly the same previous service s^- and following service s^+ with respect to the leg considered. Let s_1 and s_2 be the two varying services used by the two routes in the leg considered, therefore ω_1 has the following path $s^- \rightarrow s_1 \rightarrow s_+$ and ω_2 contains the path $s^- \rightarrow s_2 \rightarrow s_+$. s_1 and s_2 share the same starting location and destination, i.e. $o_{s_1} = o_{s_2} = d_{s^-}; d_{s_1} = d_{s_2} = o_{s^+}$. The following dominance rules are identified:

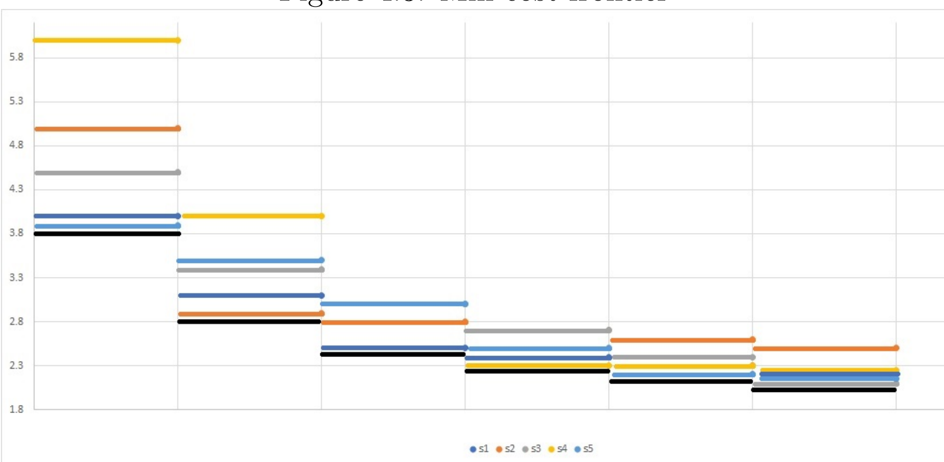
- **Mid-leg dominance:** if $c_{s_1} + w_k \cdot st_{o_{s_1}}(e_{s_1} - (e_{s^-} + t_{s^-})) + w_k \cdot st_{o_{s^+}}(e_{s^+} - (e_{s_1} + t_{s-1})) \leq c_{s_2} + w_k \cdot st_{o_{s_2}}(e_{s_2} - (e_{s^-} + t_{s^-})) + w_k \cdot st_{o_{s^+}}(e_{s^+} - (e_{s_2} + t_{s-2}))$, then route ω_1 dominates route ω_2. This dominance rule is applied to services $s \in TR_{ded}^{O-AL} \cup TR_{ded}^{O-H} \cup TR_{ded}^{H-AL}$. By checking both preceding and successive services and calculating stocking costs at both origin and destination, we can identify if a routes is dominated by another.

- **Last-leg delivery dominance:** if $e_{s_1} \leq e_{s_2} \wedge e_{s_1} + t_{s_1} \geq e_{s_2} + t_{s_2} \wedge c_{s_1} + st_{o_{s_1}} \cdot w_k \cdot (e_{s_2} - e_{s_1})) + \Delta TT^{s_1} < c_{s_2} + \Delta TT^{s_2}$ where $s_1, s_2 \in FA$, then route ω_1 dominates route ω_2. If the total cost of using s_1 is less than the cost of using s_2, then route ω_1 dominates route ω_2. This dominance rule is applied to services in FA and is a specific case of the mid-leg dominance since it computes the monetary expression of penalties incentives) due to late (early) deliveries. It is kept separated to facilitate the readability.

4.4.3 Min-cost frontier in air and LTL services

Cost dominance is the only dominance rule that can be applied to services in AC and TR_{gr}. The requirements for cost dominance though are very restrictive and situations where a service is always cheaper in every weight range are rare. What mostly happens is that some services are lower than others in certain weight ranges only. Therefore, a more suitable technique is required to effectively reduce the number of services considered. The idea is to take advantage of the situation where services are more convenient in some weight ranges only and not in all of them. In order to do that, the following procedure is devised.
Given a service s, a set of services $\hat{S} \in TR_{gr} \cup AC$ is created including all services with the same origin, destination, release time and transit time as s. If $|\hat{S}| > 1$, a virtual service vs is created where $o_{vs} = o_s, d_{vs} = d_s, e_{vs} = e_s, t_{vs} = t_s$. Then, for each weight range $r \in R$ we check which service in $\hat{S}$ is the less expensive, and use its unitary cost for the corresponding weight range as unitary cost for vs, i.e. $f_{vs,r} = \min\{f_{sr} \mid s \in \hat{S}\} \; \forall \; r \in R$. This way a min-cost frontier for all services in $\hat{S}$ is obtained. Figure 4.3 shows how the min-cost frontier is identified.

Figure 4.3: Min-cost frontier



In figure 4.3 a representation of services cost is depicted. It can be seen that each service s has a weight range r where f_{sr} is the minimum when compared to other services. The thick black line identifies the min cost frontier, which is the cost function of the newly created virtual service vs. Once the min-cost frontier is constructed, it is associated with the virtual service vs which substitutes all services in $\hat{S}$.

4.4.4 Heuristic rule

Ideally, a company that needs to ship its goods internationally relies on air transportation due to its reliability and to the fact that it is the fastest option available. Thus, requests of air transportation services are often characterized by a short transportation time. Moreover, while in other intermodality options (rail or maritime for instance), stocking costs are relatively low (container terminals usually offers a 7 days free storage, and the daily cost applied to the whole container is typically low), air transportation often presents high stocking costs, as airport cargo facilities are generally expensive. All together, it is reasonable to imagine that the best way to handle air transportation requests for international shipments is to choose a series of services which lie in a restricted time lapse within each other, since waiting long time at intermediate facilities generates high stocking and penalty costs.
These observations are at the basis of the heuristic rule that we propose. It is basically a 'rule of thumb' which is close to what is done in practice. The idea is the following. Once a service s_1 has been chosen, we restrict the choice of successive services by considering only those services which start within a given time period with respect to the end of service s_1. In practice, a service s_2 is a candidate successive service of s_1 if $e_{s_2} \in [e_{s_1} + t_{s_1}, e^{s_1} + t_{s_1} + \Delta]$.
The performance of the heuristic rule is tested for different values of Δ in Section 4.5.4. Three versions consider a fixed value for Δ (1 day, 2 days, 3 days), while three other versions consider a variable value of Δ based on the transit time required for the shipment ($(l_k - e_k)/2$, $(l_k - e_k)/3$, $(l_k - e_k)/4$). The idea is to allow a wider choice for shipments that does not require a very strict transit time, while the choice is restricted for urgent shipments.

4.5 Computational experiments

Computational tests are made on instances based on real data proposed in Chapter 3. For completeness, the characteristics of the instances are briefly described.
The instances are based on a database of 156 shipments from a north-italian freight forwarding company. The time horizon (T) is two months and is discretized in periods of half a day. All origins (set O) are in Italy and destinations (set D) are outside Europe. Set AL is composed by the airports of Malpensa, Venice and Fiumicino, while the set AD is composed by different airports worldwide. There is a single warehouse (set H) located near Bergamo. Set TR_{ded}^{O-AL} is generated by considering 1-2 dedicated transportation services from origin to airports for each shipment and set TR_{ded}^{O-H} is generated in a similar way. Set TR_{ded}^{H-AL} is composed

by the services provided by three suppliers which operate twice a day (once in the morning and once in the afternoon). For groupage services (TR_{gr}), two suppliers offer transportation services only to Milan Malpensa once a day, in the afternoon. For dedicated services, real quotations received by suppliers are considered, while for groupage services suppliers market fares are applied. Parameter η is set to three full days (6 time windows) while parameter β is set to 7 full days. The value of β considered is generous and in our experiments it happened almost always that shipments are delivered on time. As for η, its value reflects the company's practice.

Figure 4.4: Set AD

For each AoL-AoD combination (services AC), the air companies offering a connection are considered using the corresponding weekly schedule and the published market fares. For delivery services at the destination country (services FA), real quotations received by foreign agents were considered.

Instances of different sizes, $|K| = 10$, 30, 50 and 100, have been generated by randomly selecting shipments contained in the database of 156 shipments. For each value of $|K|$, 10 different instances of the same size have been generated. In Section 4.5.1 the performance of the set-partitioning formulation is evaluated by analyzing its behaviour with respect to the size of the instances. This analysis is done by looking at the dimensions of the model and the solution time. In Section 4.5.2 it is shown the effect of the dominance rules on the performance of the formulation while in Section 4.5.4 the results related to the heuristic approach presented in Section 4.4.4 are depicted.

In the following, the effectiveness of the acceleration techniques described in Sections 4.4.2 and 4.4.3 in reducing the number of routes generated by the route construction algorithm are first analyzed. Then, the results of the matheuristic algorithm for

different versions of the heuristic rule presented in Section 4.4.4 are reported.
The matheuristic algorithm has been implemented in $C\sharp$, 64-bit system, on a i3-4005U 1.7 GHz processor, 4 GB DDR3 Ram portable computer. CPLEX 12.5 has been used as MIP solver.

4.5.1 Performance of the formulation

First, the performance of the set-partitioning formulation with respect to the size of the instances is evaluated. Table 4.1 reports, for each instance, the number of variables (V), the number of constraints (C), the solution time in seconds (T) and the optimality gap (G). The last two rows report the average and standard deviation of each column, respectively.
When the solver goes out of memory, the time needed to find the best feasible solution found is checked and the results obtained are reported. Whenever data are Not Available (NA), it means that the solver is not capable of loading the model and find any feasible solution. Every instance has a maximum time limit of 1 hour.

Table 4.1: Complete enumeration performance

	$\lvert K\rvert = 10$				$\lvert K\rvert = 30$				$\lvert K\rvert = 50$				$\lvert K\rvert = 100$			
I	V ($\times 10^3$)	C($\times 10^3$)	T (sec.)	G (%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)
1	96.3	44.1	45	0.00	40.3	180.4	NA	NA	486.0	220.0	NA	NA	1008.1	656.0	NA	NA
2	99.2	39.2	30	0.00	371.2	142.7	365	9.64	426.6	174.1	NA	NA	1028.1	661.8	NA	NA
3	88.4	31.3	21	0.00	239.1	69.3	98	0.00	484.4	210.6	NA	NA	1071.0	697.3	NA	NA
4	63.1	35.5	9s	0.00	390.2	139.8	99	17.60	524.2	274.6	NA	NA	1092.2	695.0	NA	NA
5	90.1	26.9	16s	0.00	364.4	158.8	326	2.93	533.3	356.1	NA	NA	1127.0	673.4	NA	NA
6	118.4	57.4	44	0.00	270.7	97.7	94	0.00	511.0	243.2	NA	NA	1071.6	642.5	NA	NA
7	100.6	35.2	23	0.00	220.2	117.2	62	0.00	487.2	269.5	NA	NA	1146.9	732.8	NA	NA
8	134.7	27.9	44	0.00	294.8	190.5	146	0.00	517.6	243.1	NA	NA	1041.5	634.8	NA	NA
9	84.9	32.6	18	0.00	358.2	167.9	326	16.68	580.6	288.5	NA	NA	1135.4	847.2	NA	NA
10	256.0	31.1	67	0.00	279.9	130.6	93	0.00	517.5	248.8	NA	NA	1113.7	705.0	NA	NA
Avg	113.2	36.1	31.21	0.00	319.2	139.5	178.81	5.21	506.4	253.9	NA	NA	1083.5	694.6	NA	NA
St.Dev.	53.7	9.1	17.66	0.00	65.9	37.6	122.58	7.46	42.5	52.2	NA	NA	47.6	61.6	NA	NA

From Table 4.1 it is clear that the number of routes generated is too high and the set-partitioning formulation is able to solve to optimality only instances with 10 shipments. For the case where $|K| = 30$, the solver runs out of memory in the majority of the instances. For larger instances, the solver is not even able to load the formulation.
Table 4.2 shows the time needed, in seconds, to generate all the routes (TR) and the mathematical model (TM).

While the time required to generate the routes is reasonable, the time needed to generate the mathematical model is much larger, especially when the number of shipment increases. This observation motivated us in investigating the effect of

Table 4.2: CPU time for routes construction and model generation

	$\|K\| = 10$		$\|K\| = 30$		$\|K\| = 50$		$\|K\| = 100$	
I	TR(sec.)	TM(sec.)	TR(sec.)	TM(sec.)	TR(sec.)	TM(sec.)	TR(sec.)	TM($\times 10^3$ sec.)
1	1.0	64	18	537	29	798	64	2.62
2	1.2	53	16	558	20	841	44	2.76
3	0.9	40	5	276	28	947	60	3.11
4	0.7	24	14	620	40	1160	87	3.81
5	0.7	35	19	563	44	833	97	2.74
6	1.4	81	8	359	47	987	99	2.69
7	1.0	49	6	283	33	778	72	2.56
8	1.2	53	12	332	35	749	77	2.46
9	0.7	36	12	448	42	989	91	3.25
10	2.4	146	13	414	30	733	65	2.41
Avg.	1.114	58.19	12.44	439.04	34.73	881.87	75.60	2.84
St.Dev.	0.492	32.99	4.53	119.04	7.96	129.22	16.79	0.41

dominance rules. In fact, dominance rules will increase the time required to generate the feasible routes, but will reduce the number of routes generated, therefore helping in decreasing the size of the mathematical model.

4.5.2 Performance of acceleration techniques

In this section the results obtained by applying the dominance rules presented in Section 4.4.2 are shown. A comparison with both the complete enumeration approach and with the results obtained in Chapter 3 is made.
The rules are applied according to the following procedure. Cost and Faster Delivery dominances are checked before starting the route generation since they can be applied directly to the services. The other dominances are implemented during the route generation process, every time a service is selected to expand the path, we first check if it is already dominated by paths that are parts of routes already in Ω_k. If so, the path is discarded and the routes generation of this branch is interrupted. Otherwise it is checked if the path dominates any routes already in Ω_k and eventually removes them, add the service to the path and continue the routing generation. At the end of the procedure, if the now fully formed routes is not dominated, it is added to Ω_k. Table 4.3 shows the time required, in seconds, by the route construction phase (TR) and the generation of the mathematical model (TM).

As expected, checking the dominance rules increases the time required for the routes

Table 4.3: CPU time for routes construction and model generation with dominance rules

	$\lvert K\rvert = 10$		$\lvert K\rvert = 30$		$\lvert K\rvert = 50$		$\lvert K\rvert = 100$	
I	TR(sec.)	TM(sec.)	TR(sec.)	TM(sec.)	TR(sec.)	TM(sec.)	TR(sec.)	TM(sec.)
1	38	6	229	86	199	138	503	534
2	41	5	169	59	132	139	782	503
3	29	4	65	31	216	161	611	958
4	10	2	141	70	206	190	639	534
5	38	4	287	88	277	162	899	641
6	73	9	102	48	233	151	600	797
7	31	5	60	38	180	152	801	561
8	168	6	138	62	224	129	460	484
9	22	4	148	67	434	194	793	586
10	437	19	123	58	340	137	616	554
Avg.	88.6	6.5	146.1	60.6	243.9	155.3	670.7	615.2
St.Dev.	123.8	4.7	73.6	17.7	91.8	20.9	134.8	141.8

construction phase. However, since the number of routes generated is reduced, the time required to generate the mathematical model is lower.

The aim of dominance rules presented in Section 4.4.2 is discarding dominated routes so as to reduce the number of routes that should be passed to the set-partitioning formulation. The heading of the columns are as follows. N is the number of routes generated without dominance rules, D is the number of routes generated when dominance rules are applied, *red.* is the percentage reduction of routes generated with dominance rules. Table 4.4 shows the total number of routes generated by the route construction algorithm for each instance with and without dominance rules.

Table 4.4: Dominance rules performance

	$\lvert K\rvert = 10$			$\lvert K\rvert = 30$			$\lvert K\rvert = 50$			$\lvert K\rvert = 100$		
I	N ($\times 10^3$)	D($\times 10^3$)	red.(%)	N($\times 10^3$)	D($\times 10^3$)	red.(%)	N($\times 10^3$)	D($\times 10^3$)	red.(%)	N($\times 10^3$)	D($\times 10^3$)	red.(%)
1	74.4	19.0	-74.46	328.4	95.1	-71.05	395.2	$116.1 \cdot 10^3$	-70.62	759.6	227.9	-70.00
2	80.6	27.7	-65.61	310.3	91.2	-70.59	349.3	$98.5 \cdot 10^3$	-71.80	77.9	221.1	-71.60
3	72.7	19.3	-73.45	205.3	60.4	-70.56	395.5	125.2	-68.34	808.2	249.9	-69.08
4	46.2	14.6	-68.44	329.5	97.0	-70.55	411.7	124.8	-69.67	831.8	253.1	-69.57
5	75.9	22.9	-69.82	297.0	86.9	-70.76	394.7	114.5	-70.99	874.1	257.7	-70.51
6	90.8	24.8	-72.75	225.5	69.1	-69.35	398.8	119.9	-69.94	830.8	251.1	-69.77
7	82.8	24.9	-69.95	167.3	45.5	-72.78	376.9	117.6	-68.80	873.7	259.6	-70.29
8	121.3	33.4	-72.44	216.7	57.5	-73.47	418.8	135.3	-67.70	802.1	239.9	-70.09
9	68.5	26.0	-62.03	288.0	90.0	-68.74	463.9	133.5	-71.23	824.6	248.6	-69.86
10	239.7	70.4	-70.61	222.6	67.8	-69.52	417.1	123.4	-70.42	849.2	251.6	-70.38
Avg	95.3	28.3	-69.95	259.1	76.1	-70.74	402.2	120.9	-69.95	823.3	225.4	-70.12
St. Dev.	51.3	14.9	3.62	55.0	17.3	1.39	28.3	9.9	1.26	35.6	60.6	0.64

The results show that the reduction on the number of routes generated is remarkable, around 70%. Thus, it can be concluded that dominance rules effectively do their job, even if, as it will be mentioned later, this reduction is not sufficient to reduce the set of generated routes to a size that is manageable by the set-partitioning formulation.
Consequently, the time needed to generate, and solve, the mathematical model, is lower. Table 4.5 shows the performance of the set-partitioning formulation when dominance rules are applied.

Table 4.5: Performance of the set-partitioning formulation with dominance rules

	$\|K\| = 10$				$\|K\| = 30$				$\|K\| = 50$				$\|K\| = 100$			
I	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)
1	40.9	44.1	8.2	0.00	169.6	180.4	317.4	17.19	206.9	220.0	233.1	0.00	476.4	656.0	NA	NA
2	46.3	39.2	7.1	0.00	152.1	142.7	610.6	7.63	175.8	174.2	622.8	3.22	470.5	661.8	NA	NA
3	35.0	31.3	4.5	0.00	94.3	69.3	40.1	0.00	214.1	210.6	628.9	8.57	512.7	697.3	NA	NA
4	31.5	35.5	3.2	0.00	158.1	139.8	619.8	7.83	237.4	274.6	66.5	0.00	513.4	695.0	NA	NA
5	37.0	26.9	5.0	0.00	154.2	158.8	41.4	0.00	253.0	356.1	625.7	4.18	510.7	673.4	NA	NA
6	52.4	57.4	12.9	0.00	114.4	97.7	30.6	0.00	219.8	243.2	328.8	6.95	491.9	642.5	NA	NA
7	42.7	35.2	6.1	0.00	98.4	117.2	24.9	0.00	227.9	269.5	76.9	0.00	532.8	732.8	NA	NA
8	46.9	27.9	11.2	0.00	135.5	190.5	461.2	0.00	234.1	243.1	85.9	0.00	479.3	634.8	NA	NA
9	42.5	32.6	9.8	0.00	160.2	167.9	480.0	0.00	250.1	288.5	139.6	0.00	559.3	847.2	NA	NA
10	86.8	31.1	14.8	0.00	125.2	130.6	32.2	0.00	223.8	248.8	463.4	0.00	516.0	705.0	NA	NA
Avg	46.8	36.1	8.29	0.00	136.2	139.5	265.81	3.26	224.3	252.8	327.16	2.29	506.3	694.6	NA	NA
St.Dev.	16.3	9.1	3.82	0.00	26.9	37.6	258.23	5.85	22.5	49.4	240.15	3.28	27.5	61.6	NA	NA

Clearly the number of variables is much lower. The number of constraints on the other side remains unchanged, as expected, as they do not depend on the number of routes. The time needed to find the optimal solution is much lower and, when it is not possible to solve the problem to optimality as the solver runs out of memory, the optimality gap is much lower than in the case without dominance rules. For instances with $|K| = 50$ the model is able to find good solutions in reasonable times. When comparing the total time needed to solve the problem with and without dominance rules, it can be noticed that checking the dominance makes the approach slightly slower, while finding much better results on the other side. Still, it is not able to find feasible solutions for instances with $|K| = 100$. This motivates the use of the heuristic rule presented in Section 4.4.4.
Before moving to the analysis of heuristic rules, in Table 4.6 it is shown the comparison between the model proposed in Chapter 3 and the model proposed in this chapter.

T1 is the time needed to find the solution by the model proposed in Chapter 3 while T2 is the time needed by the model proposed in this chapter, when dominance rules are applied. Similarly, G1 is the optimality gap of the last solution found by the model proposed in Chapter 3 while G2 is the optimality gap of the model proposed in this chapter. For both the model proposed in this chapter and the one proposed

Table 4.6: Comparison between models performance

	$\|K\| = 10$				$\|K\| = 30$			
I	T1 (sec.)	T2(sec.)	G1(%)	G2(%)	T1(sec.)	T2(sec.)	G1(%)	G2(%)
1	3.04	8.22	0.00	0.00	920.66	317.40	0.00	17.19
2	5.46	7.05	0.00	0.00	128.14	610.55	0.00	7.63
3	2.02	4.52	0.00	0.00	25.94	40.13	0.00	0.00
4	1.38	3.23	0.00	0.00	130.01	619.82	0.00	7.83
5	1.73	5.02	0.00	0.00	15.73	41.38	0.00	0.00
6	3.98	12.94	0.00	0.00	14.24	30.59	0.00	0.00
7	1.44	6.12	0.00	0.00	6.06	24.85	0.00	0.00
8	2.37	11.24	0.00	0.00	140.22	461.15	0.00	0.00
9	1.19	9.81	0.00	0.00	146.73	480.01	0.00	0.00
10	1.18	14.77	0.00	0.00	22.32	32.17	0.00	0.00
	$\|K\| = 50$				$\|K\| = 100$			
1	97.75	233.07	0.00	0.00	213.57	NA	0.00	NA
2	956.21	622.84	0.00	3.22	307.18	NA	5.14	NA
3	57.75	628.94	0.00	8.57	306.81	NA	4.90	NA
4	48.31	66.45	0.00	0.00	267.87	NA	6.22	NA
5	506.17	625.74	2.20	4.18	308.51	NA	7.32	NA
6	784.54	328.81	0.00	6.95	308.70	NA	6.04	NA
7	65.61	76.92	0.00	0.00	207.46	NA	8.27	NA
8	161.20	85.90	0.00	0.00	306.62	NA	13.13	NA
9	286.22	139.60	0.00	0.00	182.19	NA	17.51	NA
10	509.12	463.37	0.00	0.00	211.11	NA	9.71	NA

in Chapter 3 the time limit to find the optimal solution is set to 1 hour. Even with the dominance rules the set-partitioning model is still slower and find worse solutions when compared with the previously proposed model. Heuristic rules are then added to further improve the performance of the set-partitioning model.

4.5.3 Performance of Min-cost frontier

In this section the results obtained by implementing the min-cost frontier technique, to reduce the number of AC and TR_{gr} services and thus further reduce the number of generated routes, are explored. Since in the data used to study the models there is no LTL service overlapping, the use of this technique brings no improvements to neither routes reduction nor quality of solutions found. On the other side air services are offered by a moltitude of companies and overlapping between them is far more common. Moving to the construction of the min-cost frontier presented in Section 4.4.3, its aim is to reduce the number of services in $TR_{gr} \cup AC$ that are considered when constructing the routes, so as to reduce the number of routes generated. Results are presented in Table 4.7 which shows the reduction of the number of services in the set AC using min-cost frontier. The reduction in the number of services in TR_{gr} is not reported as the number of these services is very limited in the original instances, so no saving is achieved in this set. The heading of the columns are as follows. AC is the number of services $s \in AC$, VS is the number of virtual services generated, $\Delta\%$ is the percentage reduction in the number of air services generated.

Table 4.7: Min-cost frontier performance

	$\lvert K\rvert = 10$			$\lvert K\rvert = 30$			$\lvert K\rvert = 50$			$\lvert K\rvert = 100$		
IST	AC	VS	Δ%(%)	AC	VS	Δ%(%)	AC	VS	Δ%(%)	AC	VS	Δ%(%)
1	1953	1607	-17.72	3913	3338	-14.69	4767	4132	-13.32	8107	7021	-13.40
2	1494	1220	-18.34	3603	3086	-14.35	5226	4511	-13.68	7854	6611	-15.83
3	1427	1087	-23.83	2922	2450	-16.15	5075	4228	-16.69	8275	7133	-13.80
4	1355	1095	-19.19	3922	3317	-15.43	5706	4825	-15.44	7805	6709	-14.04
5	1377	1091	-20.77	3922	3267	-16.70	5390	4578	-15.06	7758	6675	-13.96
6	2285	1857	-18.73	3436	2878	-16.24	5127	4425	-13.69	7250	6295	-13.17
7	1651	1311	-20.59	3740	3102	-17.06	5573	4849	-12.99	7882	6751	-14.35
8	1105	865	-21.72	3944	3328	-15.62	4837	4084	-15.57	7577	6513	-14.04
9	1501	1099	-26.78	3873	3290	-15.05	5561	4651	-16.36	7713	6595	-14.50
10	1615	1259	-22.04	3756	3224	-14.16	4755	4020	-15.46	8010	6881	-14.09
Avg.	1576.3	1249.1	-20.97	3703.1	3128	-15.55	5201.7	4430.3	-14.83	7823.1	6718.4	-14.12
St. Dev.	315.72	273.40	2.64	303.72	264.43	0.94	331.73	287.46	1.24	270.16	232.63	0.68

The reduction in the number of air services used to generate routes is evident but not substantial. Moreover it wield the better effect on instances with a lower number of shipments, where dominance rules already are sufficient to ensure optimal results. On the other side, solutions found for bigger instances are not improved noticeably and the reduction in the number of services in AC considered is less effective. This is due to the structure of the database used to generate the models. The data was selected from a real world scenario, but it was already trimmed in order to evaluate the effect of the model to generate good solutions for the company in non trivial instances. For instance, for shipment destined to uncommon area, where the chance of consolidation is limited, the collection of data focused on offering services with different starting time and transit time, that is a situation where the construction of the min-cost frontier does not reduce the number of services. For shipments with a higher consolidation chance, however, the number of overlapping service is greater since part of the study focuses on checking the use of consolidation in solutions,

therefore the reduction of services is more prominent. Unfortunately, the former situation is far more common, with a higher number of non overlapping services.
To better explore the effectiveness of the min-cost frontier we build another instance based on real world data, where overlapping services, considering the time windows length of half a day, are fairly common. The database is composed of 100 shipment requests ($|C| = 100$) with randomly generated origin location in Italy, delivery location chosen between areas near four big hub airports (JFK, LAX, PVG and DWC), release time and due delivery time. Services are then generated accordingly, based on real world data considering actual schedules from all the major companies serving the airports. For each Aol-Aod pair the schedules of ten air companies are selected and implemented, for a total of 2078 services $s \in AC$. The complete enumeration procedure generates 1,075,213 feasible tours and CPLEX is not able to load the mathematical model. By adding the dominance rules the number of feasible routes generated drop to 217,217 but still CPLEX is not able to load the model. However, when implementing the min-cost frontier technique, there are 828 virtual services (a reduction of the 60.15% from the original number of air services, 2078) and the number of feasible routes shrink to 131,036, a reduction of 87.81% if compared with the complete enumeration technique and of the 39.67% if compared with the model generated using the dominance rules only. CPLEX load the model and is able to find a solution with an optimality gap of 0.56% before running out of memory after approximately 217 seconds. It is clear that the more sparse are the air service considered, the less useful this technique is. On the other side, real world application should benefit greatly from the use of the min-cost frontier since overlapping in schedules between different companies are far more common.
Still, preliminary experiments show that combining both acceleration techniques is not sufficient to reduce the number of routes generated to a size which is manageable by the set-partitioning formulation. In fact, no instance with $|K| = 100$ could be solved as well as many instances with $|K| = 50$ and some instances with $|K| = 30$. Thus, we now focus on the matheuristic algorithm which is been devised to manage large-size instances.

4.5.4 Performance of the matheuristic algorithm

In this section the results obtained by applying the matheuristic algorithm using the heuristic rule presented in Section 4.4.4 for different values of Δ are presented. In particular, we consider $\Delta = 1, 2, 3$ days (respectively 2,4 and 6 half-days) and $\Delta = (l_k - e_k)/4$, $\Delta = (l_k - e_k)/3$ and $\Delta = (l_k - e_k)/2$. Acceleration techniques rules are still applied. In the following, this notation will be used:

- 1D corresponds to the heuristic with $\Delta = 1$ day.
- 2D corresponds to the heuristic with $\Delta = 2$ days.
- 3D corresponds to the heuristic with $\Delta = 3$ days.
- 1Q corresponds to the heuristic with $\Delta = (l_k - e_k)/4$ half-days.
- 1T corresponds to the heuristic with $\Delta = (l_k - e_k)/3$ half-days.
- 1H corresponds to the heuristic with $\Delta = (l_k - e_k)/2$ half-days.

Results are presented in Tables 4.8 and 4.9 for constant and variable values of Δ, respectively, where I is the instance number, V is the number of variables in the set-partitioning formulation, C is the number of constraints, T is the solution time in seconds solution time, G is the percentage optimality gap at termination. Note that when G is positive, it means that CPLEX run out of memory. It can be seen that the matheuristic is effective in producing a set of routes of reasonable size. In fact, almost all instances are solved to optimality and, when not, the optimality gap is reduced (with the only exception of instances 7 and 9 with $|K| = 100$ and D3). Note that, when G is equal to 0, this does not mean that the corresponding solution is optimal, but, instead, that the best solution from the set of routes passed to the formulation has been found.

It is quite interesting to note that, when $|K| = 100$, 2D takes longer than 3D and 1T takes longer than 1H. This is due to the fact that, for 3D and 1H, CPLEX runs out of memory faster than for 2D and 1T.
Figure 4.5 shows a graphical representation of the average time needed by the six versions of the heuristic to find the best solution.

With all the six values of Δ the model runs much faster than without heuristic rules and is always able to find at least a feasible solution.
Clearly the one day scenario offers better performances, lower solution times and is always capable of finding the optimal solution of the model generated through the heuristic approach. The reason for this difference in performance is given by the much lower number of feasible routes generated.
Table 4.10 shows this number for the six values of Δ. The differences in the number of routes generated is reflected on the time needed to construct routes and to generate the model as shown in Figure 4.6. As expected, it reflects the behavior of solution time: the lower is the number of routes generated, the lower is the solution time. On the other side, sacrificing too many routes increases the risk of finding sub-optimal solutions in comparison with a wider generation of routes.

Table 4.8: Performance of heuristics with constant Δ

	$\lvert K\rvert = 10$				$\lvert K\rvert = 30$				$\lvert K\rvert = 50$				$\lvert K\rvert = 100$			
I	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)
	1D															
1	23.1	44.1	1.8	0.00	78.2	180.4	6.8	0.00	95.9	220.0	5.5	0.00	257.2	656.0	34.7	0.00
2	19.7	39.2	0.9	0.00	64.5	142.7	5.2	0.00	82.0	174.2	6.1	0.00	257.9	661.8	58.5	0.00
3	16.3	31.3	0.7	0.00	36.8	69.3	2.6	0.00	92.8	210.6	5.4	0.00	272.0	697.3	37.1	0.00
4	17.4	35.5	0.6	0.00	64.8	139.7	3.2	0.00	118.3	274.6	6.1	0.00	269.5	695.0	27.3	0.00
5	15.0	26.9	0.7	0.00	71.4	158.8	3.5	0.00	143.3	356.1	7.8	0.00	262.7	673.4	30.5	0.00
6	28.3	57.4	1.1	0.00	47.9	97.7	2.7	0.00	105.3	243.2	6.9	0.00	250.3	642.5	15.1	0.00
7	18.8	35.2	0.9	0.00	54.4	117.2	2.1	0.00	114.9	269.4	5.2	0.00	283.5	732.8	43.9	0.00
8	14.8	27.9	1.0	0.00	80.0	190.5	4.2	0.00	103.7	243.1	5.7	0.00	248.7	634.8	32.3	0.00
9	17.4	32.6	0.6	0.00	73.6	167.9	4.5	0.00	120.8	288.5	7.0	0.00	320.7	847.2	61.4	0.00
10	17.5	31.1	0.9	0.00	59.8	130.6	2.6	0.00	105.3	248.8	7.7	0.00	273.2	705.0	30.2	0.00
Avg	18.8	36.1	0.9	0.00	63.2	139.5	3.7	0.00	108.2	252.8	6.3	0.00	269.6	665.8	37.1	0.00
St.Dev.	4.1	9.1	0.3	0.00	13.8	37.6	1.4	0.00	17.2	49.4	0.9	0.00	21.0	146.5	14.1	0.00
	2D															
1	25.2	44.1	1.4	0.00	85.3	180.4	19.6	0.00	107.6	220.0	18.8	0.00	279.4	656.0	115.9	0.00
2	22.9	39.2	1.7	0.00	72.7	142.7	15.8	0.00	91.8	174.2	20.4	0.00	278.0	661.8	135.5	0.00
3	17.9	31.3	1.1	0.00	42.9	69.3	4.8	0.00	104.9	210.6	29.8	0.00	293.3	697.3	298.4	0.00
4	18.3	35.5	0.8	0.00	73.8	139.8	9.3	0.00	131.5	274.6	14.6	0.00	291.4	695.0	156.3	0.00
5	16.8	26.9	1.2	0.00	79.9	158.8	9.6	0.00	154.8	356.1	49.4	0.00	285.0	673.4	109.7	0.00
6	30.1	57.4	1.5	0.00	55.7	97.7	8.1	0.00	118.0	243.2	28.8	0.00	272.2	642.5	121.1	0.00
7	20.5	35.2	1.2	0.00	58.6	117.2	3.2	0.00	125.2	269.5	14.1	0.00	307.6	732.8	619.3	0.30
8	18.6	27.9	2.4	0.00	85.1	190.5	12.8	0.00	115.5	243.1	22.3	0.00	270.7	634.8	569.7	0.00
9	20.2	32.6	1.3	0.00	81.8	167.9	17.7	0.00	132.0	288.5	20.7	0.00	344.7	847.2	114.6	3.70
10	20.3	31.1	1.0	0.000	66.1	130.6	4.9	0.00	116.0	248.8	23.5	0.00	293.1	705.0	382.2	0.00
Avg	21.1	36.1	1.4	0.00	70.2	139.5	10.6	0.00	119.7	252.8	24.2	0.00	291.6	694.6	262.3	0.40
St.Dev.	4.0	9.1	0.4	0.00	14.2	37.6	5.7	0.00	17.4	49.4	10.2	0.00	21.8	61.6	197.6	1.16
	3D															
1	29.0	44.1	5.7	0.00	99.6	180.4	37.3	0.00	131.4	220.0	40.1	0.00	322.2	656.0	584.7	0.00
2	28.7	39.2	3.4	0.00	88.4	142.7	18.5	0.00	110.9	174.2	70.5	0.00	319.8	661.8	538.1	0.99
3	21.2	31.3	4.8	0.00	55.0	69.3	20.8	0.00	128.0	210.6	61.2	0.00	337.8	697.3	77.0	5.25
4	20.6	35.5	7.8	0.00	91.3	139.8	31.1	0.00	157.5	274.6	22.5	0.00	336.9	695.0	121.5	2.67
5	20.5	26.9	2.4	0.00	96.0	158.8	14.8	0.00	178.3	356.1	84.8	0.00	330.6	673.4	124.3	3.68
6	34.6	57.4	8.2	0.00	69.0	97.7	12.9	0.00	142.2	243.2	69.5	0.00	315.1	642.5	330.7	1.07
7	24.5	35.2	4.0	0.00	66.3	117.2	8.8	0.00	146.9	269.5	22.6	0.00	355.9	732.8	75.9	10.98
8	26.0	27.9	4.0	0.00	94.9	190.5	37.8	0.00	139.3	243.1	44.9	0.00	315.7	634.8	118.5	3.42
9	25.6	32.6	2.8	0.00	98.3	167.9	34.4	0.00	154.5	288.5	34.9	0.00	392.3	847.2	81.2	14.00
10	26.4	31.1	2.1	0.00	78.8	130.6	11.4	0.00	137.3	248.8	37.7	0.00	334.4	705.0	173.9	2.58
Avg	25.7	36.1	4.5	0.00	83.8	139.5	22.8	0.00	142.6	252.8	48.9	0.00	336.1	694.6	222.6	4.47
St.Dev.	4.4	9.1	2.1	0.00	15.6	37.6	11.3	0.00	18.4	49.4	21.5	0.00	23.3	61.6	193.9	4.55

Focusing on solution values, the results are reported in Table 4.11. The table compares the value of the solutions obtained with the matheuristic by applying the six different rules considered with the value of the solution provided by the problem formulation proposed in Chapter 3 (C3 in the table). The table reports the percentage deviation with respect to the best solution found in Chapter 3 (the optimality gap is reported) for each instance.

Unsurprisingly, in 1D, the optimal solution found by the heuristic model is slightly worse than the ones obtained by the other methods. However, the gap is rarely

Table 4.9: Performance of heuristics with variable Δ

	$\lvert K\rvert = 10$				$\lvert K\rvert = 30$				$\lvert K\rvert = 50$				$\lvert K\rvert = 100$			
I	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)	V($\times 10^3$)	C($\times 10^3$)	T(sec.)	G(%)
	1Q															
1	23.4	44.1	1.1	0.00	81.5	180.4	6.2	0.00	98.9	220.0	3.7	0.00	262.9	656.0	22.9	0.00
2	20.4	39.2	0.7	0.00	67.8	142.7	2.8	0.00	85.5	174.2	8.3	0.00	263.7	661.8	19.6	0.00
3	17.1	31.3	0.5	0.00	38.5	69.3	1.3	0.00	95.6	210.6	4.8	0.00	278.7	697.3	24.1	0.00
4	17.6	35.5	0.4	0.00	67.8	139.8	2.5	0.00	122.7	274.6	4.6	0.00	276.0	695.0	38.5	0.00
5	15.8	26.9	0.4	0.00	74.3	158.8	2.6	0.00	147.1	356.1	8.6	0.00	271.7	673.4	28.4	0.00
6	28.8	57.4	0.7	0.00	50.2	97.7	1.8	0.00	110.0	243.2	9.3	0.00	257.7	642.5	18.9	0.00
7	19.5	35.2	0.4	0.00	56.1	117.2	1.4	0.00	117.3	269.5	3.1	0.00	291.3	732.8	139.9	0.00
8	16.2	27.9	0.9	0.00	82.3	190.5	2.5	0.00	106.8	243.1	4.4	0.00	255.3	634.8	126.2	0.00
9	17.4	32.6	0.4	0.00	75.8	167.9	5.1	0.00	125.3	288.5	6.8	0.00	327.3	847.2	107.6	0.00
10	20.3	31.1	0.6	0.00	61.2	130.6	2.2	0.00	109.4	248.8	5.9	0.00	280.4	705.0	41.4	0.00
Avg	19.6	36.1	0.6	0.00	65.5	139.5	2.8	0.00	111.9	252.8	5.9	0.00	276.5	694.6	56.8	0.00
St.Dev.	4.0	9.1	0.2	0.00	14.2	37.6	1.6	0.00	17.4	49.4	2.2	0.00	21.1	61.6	48.0	0.00
	1T															
1	24.7	44.1	1.2	0.00	88.2	180.4	33.3	0.00	106.0	220.0	10.2	0.00	276.4	656.0	604.6	1.23
2	21.9	39.2	1.2	0.00	73.9	142.7	15.2	0.00	92.0	174.2	26.1	0.00	277.6	661.8	77.1	0.00
3	18.4	31.3	0.6	0.00	42.5	69.3	4.8	0.00	102.8	210.6	15.2	0.00	293.9	697.3	50.7	0.00
4	18.2	35.5	0.5	0.00	73.3	139.8	9.4	0.00	130.7	274.6	7.3	0.00	291.8	695.0	158.4	0.00
5	17.2	26.9	0.6	0.00	80.3	158.8	4.0	0.00	155.2	356.1	34.8	0.00	288.9	673.4	55.7	0.00
6	30.3	57.4	1.8	0.00	54.8	97.7	3.8	0.00	118.8	243.2	13.3	0.00	272.5	642.5	39.4	0.00
7	21.0	35.2	0.7	0.00	59.0	117.2	1.8	0.00	124.4	269.5	4.2	0.00	308.9	732.8	308.3	0.70
8	19.6	27.9	1.4	0.00	86.0	190.5	8.0	0.00	113.9	243.1	9.5	0.00	270.0	634.8	349.1	0.00
9	18.2	32.6	0.7	0.00	81.0	167.9	7.1	0.00	133.7	288.5	7.5	0.00	342.8	847.2	205.9	2.13
10	24.1	31.1	1.0	0.00	66.0	130.6	2.4	0.00	118.3	248.8	11.9	0.00	294.4	705.0	272.0	0.00
Avg	21.4	36.1	1.0	0.00	70.5	139.5	9.0	0.00	119.6	252.8	14.0	0.00	291.7	694.6	212.1	0.41
St.Dev.	4.1	9.1	0.4	0.00	14.8	37.6	9.4	0.00	17.9	49.4	9.4	0.00	21.6	61.6	178.6	0.74
	1H															
1	30.4	44.1	2.4	0.00	109.2	180.4	63.6	0.00	128.4	220.0	18.2	0.00	322.0	656.0	76.6	4.63
2	27.2	39.2	3.7	0.00	92.1	142.7	30.3	0.00	112.1	174.2	68.4	0.00	321.5	661.8	109.3	3.35
3	22.6	31.3	2.1	0.00	54.6	69.3	7.1	0.00	125.6	210.6	154.9	0.00	345.6	697.3	107.0	2.45
4	20.8	35.5	1.0	0.00	91.5	139.8	302.9	0.00	158.5	274.6	12.0	0.00	341.1	695.0	157.1	3.13
5	22.1	26.9	2.6	0.00	99.0	158.8	21.3	0.00	180.6	356.1	98.6	0.00	344.3	673.4	157.3	3.43
6	35.4	57.4	6.3	0.00	69.1	97.7	6.5	0.00	146.8	243.2	65.2	0.00	321.1	642.5	156.4	2.85
7	25.7	35.2	2.9	0.00	68.2	117.2	6.9	0.00	146.0	269.5	10.4	0.00	362.2	732.8	77.1	6.36
8	26.7	27.9	5.1	0.00	97.6	190.5	16.5	0.00	137.9	243.1	22.6	0.00	318.4	634.8	156.7	2.96
9	22.2	32.6	2.4	0.00	97.7	167.9	222.2	0.00	160.4	288.5	19.1	0.00	391.2	847.2	77.0	4.30
10	36.2	31.1	3.9	0.00	78.4	130.6	4.8	0.00	143.7	248.8	16.4	0.00	343.2	705.0	76.5	6.20
Avg	26.9	36.1	3.2	0.00	85.7	139.5	68.2	0.00	144.0	252.8	48.6	0.00	341.0	694.6	115.1	3.97
St.Dev.	5.5	9.1	1.5	0.00	17.3	37.6	105.6	0.00	19.6	49.4	48.0	0.00	22.8	61.6	37.9	1.38

larger than 1% and it is above 5% in one case only. The difference in percentage is usually around 1%-3% from the best solution found, but on the other side it offers fast times to find the solution. For all the remaining heuristic rules, the gap is always lower than 3%. In 2D, the gap with respect to the best solution found is lower with respect to D1. It can also be noted that D2 is the heuristic rule providing the best results for $|K| = 100$. In 3D, the heuristic model finds its optimal solution in a good number of instances, but at the cost of worse performances, especially when $|K| = 100$ where optimality gaps are fairly high and the solution is not always better than the one found by the alternative rules. The rules with a variable value

Figure 4.5: Average solution times

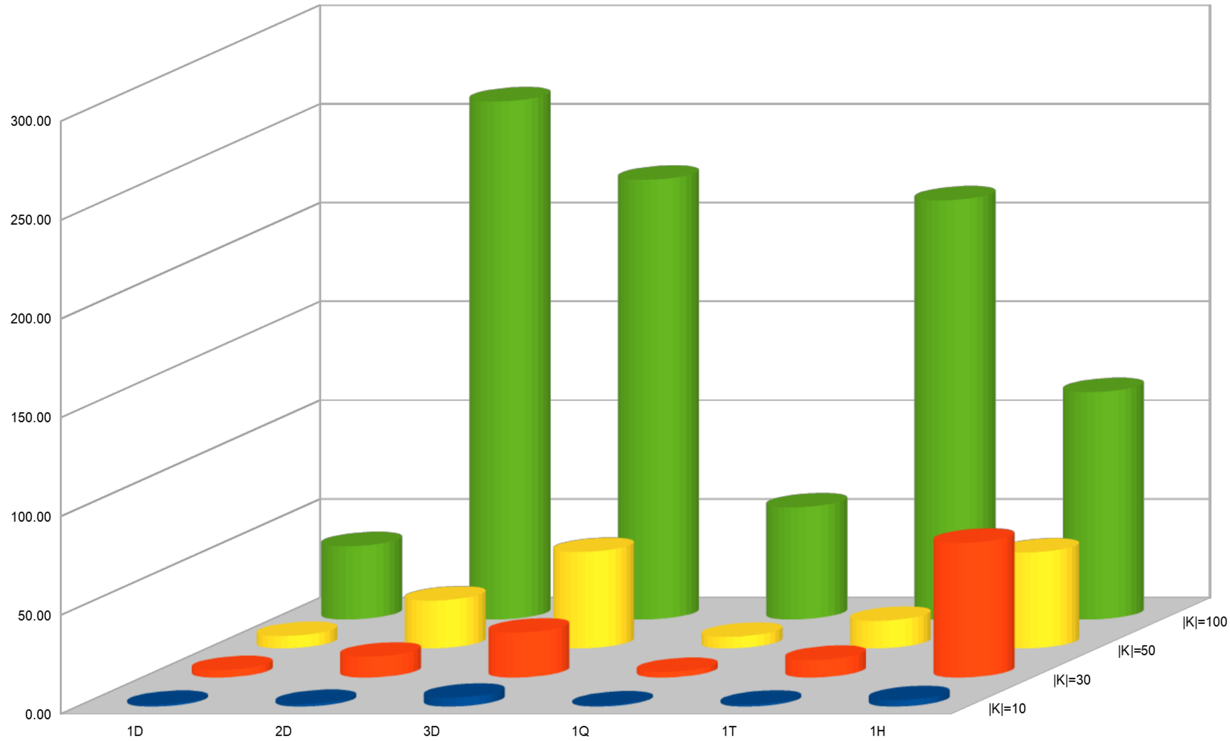
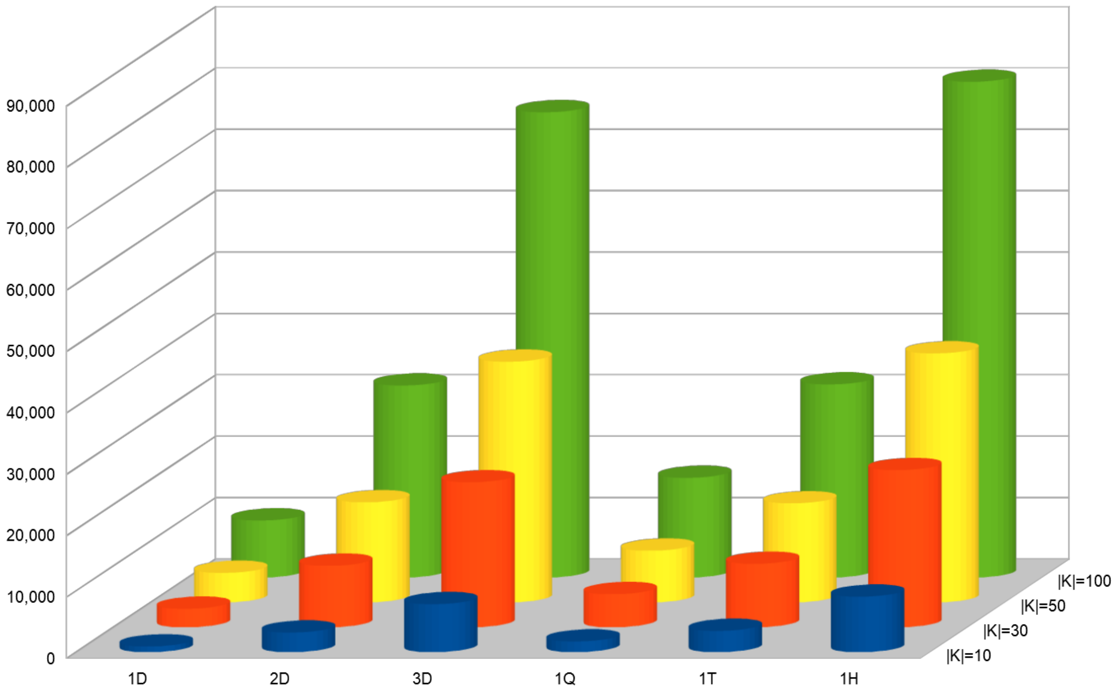


Figure 4.6: Number of routes generated



of Δ perform better than 1D but worse than both 2D and 3D, with 1H being the best among the three. We suppose that this is due to the fact that when $l_k - e_k$ is high it allows the search for a much wider spectrum of feasible routes which do not

Table 4.10: Number of routes generated with different values of Δ

	$\lvert K \rvert = 10$						$\lvert K \rvert = 30$					
I	1D	2D	3D	1Q	1T	1H	1D	2D	3D	1Q	1T	1H
1	1141	3262	7092	1406	2721	8427	3700	10705	25071	6938	13636	34618
2	1109	4298	10131	1767	3342	8602	3669	11846	27550	6922	13016	31232
3	590	2130	5462	1401	2621	6882	2928	8977	21153	4651	8572	20759
4	464	1420	3718	673	1285	3898	3812	12736	30252	6756	12243	30420
5	928	2698	6351	1691	3079	7978	4071	12509	28637	6909	12933	31629
6	681	2476	7048	1186	2742	7781	2684	10425	23777	4924	9577	23853
7	919	2662	6610	1674	3160	7883	1576	5720	13501	3257	6141	15384
8	1384	5189	12550	2727	6137	13286	1961	7048	16906	4296	7970	19571
9	922	3756	9187	961	1796	5750	3360	11562	28070	5610	10763	27518
10	1148	3971	9989	3928	7733	19832	2466	8725	21392	3792	8609	21082
Avg	929	3186	7814	1741	3462	9032	3023	10025	23631	5406	10346	25607
St. Dev.	269	1070	2478	897	1869	4255	798	2236	5148	1343	2419	6033
	$\lvert K \rvert = 50$						$\lvert K \rvert = 100$					
1	5010	16724	40592	8054	15096	37504	8719	30969	73730	14516	27962	73363
2	4671	14507	33637	8240	14746	34809	8518	28641	70402	14286	28202	72085
3	3956	15955	39140	6746	13887	36723	9149	30443	74985	15904	31116	82776
4	5778	18979	44926	10216	18159	45946	9187	31091	76603	15658	31467	80733
5	4835	16327	39800	8550	16694	42132	9778	32108	77689	18778	35946	91337
6	5357	18122	42269	10082	18859	46840	9473	31451	74300	16965	31759	8,321
7	4552	14919	36570	6995	14055	35708	10262	34336	82664	18109	35640	88987
8	4904	16661	40515	7936	15043	39117	9272	31297	76280	15858	30527	78932
9	4231	15376	37914	8679	17086	43766	9947	33950	81528	16584	32074	80419
10	4932	15617	36913	8936	17874	43256	8785	28680	69968	15950	30014	78776
Avg	4823	16319	39228	8443	16150	40580	9309	31297	75815	16261	31471	80773
St. Dev.	495	1318	3016	1075	1713	4138	534	1782	3933	1343	2530	5667

improve the solution and negatively impact on model performance. On the other side, when $l_k - e_k$ is low and thus a fast service is required, the search is too much restricted, not allowing to find good routes. Overall, assigning a constant value of Δ equal to two days appears to be the best choice when taking into account the trade-off between solution quality and model performance, as generation and solution times are reasonably limited and the solutions found are not far from the optimal. For large instance this value of delta often generates the best results in terms of solution quality. Solutions found by the model with $\Delta = 1$ day are still viable for the company and can be considered when solution time is extremely important and the number of shipments to be considered is high. Gaps from the optimal solution

Table 4.11: Comparison of solution values

	$\|K\| = 10$						
I	C3 (%)	1D(%)	2D(%)	3D(%)	1Q(%)	1T(%)	1H(%)
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.10	0.00	0.00	0.00	0.00	0.00
3	0.00	0.03	0.30	0.26	0.08	0.40	0.34
4	0.00	0.44	0.29	0.00	0.70	0.70	0.84
5	0.00	0.27	0.00	0.00	0.46	0.37	0.37
6	0.00	0.26	0.18	0.18	0.50	0.46	0.46
7	0.00	0.42	0.03	0.03	0.19	0.13	0.02
8	0.00	6.55	0.23	0.00	0.37	0.26	0.09
9	0.00	0.36	0.00	0.00	0.05	0.05	0.04
10	0.00	1.66	0.41	0.33	0.17	0.28	0.79
Avg.	0.00	1.01	0.14	0.08	0.25	0.27	0.30
St. Dev	0.00	1.90	0.15	0.12	0.23	0.21	0.30
	$\|K\| = 30$						
1	0.00	1.58	0.21	0.19	0.34	0.24	0.24
2	0.00	1.40	0.83	0.82	1.36	1.30	1.04
3	0.00	1.61	0.13	0.12	0.39	0.22	0.15
4	0.00	2.93	0.51	0.47	1.22	1.20	0.77
5	0.00	0.49	0.27	0.27	0.88	0.64	0.69
6	0.00	2.56	0.43	0.00	0.82	0.88	0.60
7	0.00	1.62	0.08	0.00	0.29	0.29	0.27
8	0.00	0.13	0.06	0.00	0.31	0.32	0.32
9	0.00	0.46	0.24	0.18	0.52	0.42	0.19
10	0.00	1.79	0.34	0.00	0.53	0.37	0.37
Avg.	0.00	1.46	0.31	0.21	0.67	0.59	0.46
St. Dev	0.00	0.85	0.22	0.25	0.37	0.38	0.28
	$\|K\| = 50$						
1	0.00	0.22	0.08	0.01	0.57	0.41	0.42
2	0.00	2.29	2.13	2.01	2.56	2.55	2.50
3	0.00	2.36	2.10	2.04	2.59	2.59	2.48
4	0.00	0.33	0.10	0.01	0.43	0.33	0.25
5	2.20	2.11	2.07	2.05	2.36	2.31	2.31
6	0.00	3.24	2.04	1.98	2.44	2.40	2.31
7	0.00	0.13	0.04	0.02	0.24	0.17	0.22
8	0.00	0.12	0.01	0.00	0.60	0.58	0.57
9	0.00	0.51	0.09	0.05	0.66	0.56	0.47
10	0.00	0.16	0.03	0.01	0.25	0.17	0.07
Avg.	0.22	1.15	0.87	0.82	1.27	1.21	1.16
St. Dev	0.66	1.14	0.99	0.98	1.00	1.03	1.02
	$\|K\| = 100$						
1	0.00	0.92	0.59	0.53	1.13	1.02	0.86
2	5.14	-0.97	-1.69	-1.70	-1.34	-1.47	-1.39
3	4.90	-1.20	-1.96	-1.70	-1.39	-1.52	-1.64
4	6.22	-1.65	-2.39	-2.29	-1.89	-1.96	-2.06
5	7.32	-1.78	-2.55	-2.02	-2.15	-2.28	-2.31
6	6.04	-1.37	-2.05	-2.13	-1.60	-1.68	-1.86
7	8.27	-1.14	-1.87	-1.16	-1.47	-1.56	-1.53
8	13.13	-2.69	-3.01	-2.75	-2.50	-2.79	-2.77
9	17.51	-5.46	-5.60	-4.73	-5.32	-5.40	-5.36
10	9.71	-2.37	-3.13	-3.16	-2.75	-2.84	-2.86
Avg.	7.82	-1.77	-2.37	-2.11	-1.93	-2.05	-2.09
St. Dev	4.57	1.53	1.46	1.29	1.51	1.51	1.47

are limited and the reduced solution times are an incentive for the use of such an heuristic approach.

Table 4.12: Comparison of solution values for $|K| = 100$ between models

IST	M1 ($\times 10^3$)	1D($\times 10^3$)	Δ 1D(%)	2D($\times 10^3$)	Δ 2D(%)	3D($\times 10^3$)	Δ 3D (%)
1	249.51	243.36	-2.466	242.57	-2.780	242.43	-2.840
2	219.82	217.68	-0.974	216.09	-1.694	216.08	-1.700
3	256.83	253.75	-1.198	251.79	-1.961	252.47	-1.698
4	267.86	263.45	-1.649	261.47	-2.387	261.73	-2.290
5	255.37	250.82	-1.781	248.87	-2.546	250.20	-2.023
6	227.76	224.64	-1.370	223.09	-2.051	222.92	-2.128
7	258.01	255.07	-1.139	253.17	-1.875	255.02	-1.156
8	232.11	225.86	-2.692	225.12	-3.009	225.72	-2.750
9	263.68	249.28	-5.458	248.91	-5.599	251.19	-4.733
10	241.53	235.80	-2.373	233.97	-3.133	233.91	-3.156
Avg.	247.25	241.97	-2.110	240.51	-2.704	241.17	-2.447
St.Dev	15.39	14.47	1.252	14.32	1.071	14.76	0.952

In Table 4.12 value of the solutions found when $\Delta = 1, 2, 3$ (columns 1D, 2D and 3D) are compared with the value obtained in Chapter 3 (column M1) for the case with $|C| = 100$, for which we have no comparison against 'N' or 'D'. The results show that the three heuristic models always improve the solution found by the exact formulation proposed in Chapter 3 (which did not find the optimal solutions for these instances), thus confirming that the approach is promising for finding high-quality solution for the problem in reasonable time when the size of the instances increases.

Finally, we examined the performance of the heuristic models when compared with the solutions implemented by the company that inspired this work and provided the data. The average difference in cost for each approach studied is reported.

Table 4.13: Comparison with company's solutions

	AP19(%)	1D(%)	2D(%)	3D(%)	$(l_k - e_k)/4$(%)	$(l_k - e_k)/3$(%)	$(l_k - e_k)/2$(%)
$\|C\| = 10$	-12.74	-11.72	-12.68	-12.72	-12.55	-12.53	-12.49
$\|C\| = 30$	-12.29	-10.64	-11.97	-12.08	-11.54	-11.65	-11.84
$\|C\| = 50$	-10.92	-9.74	-9.78	-10.13	-9.66	-9.71	-9.86
$\|C\| = 100$	-11.26	-13.40	-14.01	-13.87	-13.71	-13.82	-13.87

The results show that, despite being based on simple heuristic rules, the matheuristic provides much better results with respect to the solutions implemented by the company. The bigger is the size of the problem considered (i.e. more shipments and a larger variety of services) the more suitable the heuristic approach becomes, giving better results than the exact method, as shown in Table 4.11. The reason for the cost reduction is mainly due to the fact that the models solve the problem by considering all shipments and determining the best solution overall, while the

Table 4.14: Comparison of solutions costs for $|K| = 100$ between models

$\Delta = 1$			
IST	COST MODEL	COST COMPANY	Δ% COST
1	253,580	300,771	-15.69%
2	228,451	277,995	-17.82%
3	255,778	314,716	-18.73%
4	264,913	319,596	-16.80%
5	260,216	324,221	-18.56%
6	234,672	288,906	-18.77%
7	264,145	325,020	-18.73%
8	236,309	282,991	-16.50%
9	258,711	309,006	-16.28%
10	245,346	303,126	-19.06%
Avg.	250,212.17	304,634.80	-17.69%
St. Dev.	13,152.60	16,952.50	1.26%
$\Delta = 2$			
IST	COST MODEL	COST COMPANY	Δ% COST
1	251,694	300,771	-16.32%
2	226,393	277,995	-18.56%
3	255,078	314,716	-18.95%
4	263,781	319,596	-17.46%
5	258,623	324,221	-20.23%
6	233,115	288,906	-19.31%
7	262,502	325,020	-19.24%
8	234,789	282,991	-17.03%
9	258,011	309,006	-16.50%
10	243,696	303,126	-19.61%
Avg.	248,768.42	304,634.80	-18.32%
St. Dev.	13,382.30	16,952.50	1.39%
$\Delta = 3$			
IST	COST MODEL	COST COMPANY	Δ% COST
1	251,468	300,771	-16.39%
2	226,273	277,995	-18.61%
3	254,158	314,716	-19.24%
4	263,201	319,596	-17.65%
5	258,447	324,221	-20.29%
6	233,115	288,906	-19.31%
7	261,974	325,020	-19.40%
8	239,498	282,991	-14.97%
9	257,516	309,006	-16.66%
10	242,809	303,126	-19.90%
Avg.	248,846.02	304,634.80	-18.24%
St. Dev.	12,744.23	16,952.50	1.75%

company operators mainly focuses their effort on a single shipment base. A wider point of view requires complex solution methodologies (like the solution of a MILP) which are not currently available at the company where, instead, the optimization is done for each shipment separately, thus loosing the advantages of consolidation.

4.6 Final Remarks

In this chapter it has been studied the Air Transport Freight Forwarder Service Problem (ATFFSP) which is the problem faced by a freight forwarding company which needs to send different shipments from origins to destination at minimum cost and using different services, among which air transportation. A matheuristic algorithm based on a set-partitioning formulation and different rules for generating the set of routes is preseted. Tests have been done on instances generated from real data and the matheuristic has been compared against the exact approach proposed in Chapter 3. The results show that the matheuristic provides good results in reasonable suitable for the company computing times, thus being ideal for dealing with practical size problems.
Given the explosion of fast delivery services at a global level, driven by e-commerce growing, international air freight transportation will play a key role in the near future. As a consequence, all related intermediaries, like freight forwarders, will expand their business too. What is shown in this chapter, as introduced in Chapter 3, is that the freight forwarding problem is a complex problem which needs appropriate and ad-hoc solution methods. Thus, the contribution of this chapter goes in the direction of enriching the scientific work related to this field.

Chapter 5

The Air Transport Unit Consolidation Problem

Abstract

Consolidation of loose packages into transport units is a fundamental activity offered by logistics service providers. Moving the transport units is faster (multiple packages are loaded with one movimentation only, instead of having one load operation for each package), safer (chances of damage to packages and loss of them is greatly reduced) and cheaper. One of the typical objective of consolidation problems is the minimization of the number of transport unit used, e.g. containers. In air transportation, however, transport units have multiple aspects which concur in the calculation of the service cost and thus optimization in the number and characteristics of the transport unit is required. In this chapter, an algorithm to solve a three dimensional bin packing problem is presented. The objective is the minimization of the transport cost by means of air transportation while keeping into account various operational aspects.

Keywords: Air transportation, 3D-BPP, Extreme Points, Local Search.

5.1 Introduction

Freight forwarders handle international shipments for their customers and focus their activity on offering the most complete logistic service from origin to destination. This involves not only the management of documental operations and the physical transfer of goods, but also often includes a series of secondary logistic operations (packaging and labelling are just some examples). One of the activities carried out is the consolidation of loose packages into transport units (TU). For air shipments TUs are usually pallets of various dimensions and crates. Since most of the times shipper companies are not able to consolidate themselves the goods of which the shipment is composed, freight forwarders spend a high amount of time carrying out this operation. Choosing the number and type of TU to be used is not a simple choice and it requires the consideration of different aspects. Thus, optimizing such task will result in better solutions and less time spent on it, giving the chance to operators to focus on other aspects of the shipment.
The first feature to be considered is that the way loose packages are consolidated together impacts the management of the shipment and its cost. The most evident reason behind consolidation in TU is that the movement of one single TU is not only faster, more efficient and cheaper than handling a higher number of packages, it also increases the safety of the shipment since it is more difficult for material to go missing if safely consolidated in TUs. Moreover, since the information included in the documentation must be aligned to the characteristics of the shipment, controls by any monitoring organizations (customs, FDA, police, etc.) are easier, and thus, faster.
TUs can have different dimensions and weight capacities. We assume the measures are expressed in centimeters and in the width x length x height format, with the latter sometimes not reported. The most common TU used is pallets. EUR and EUR1 pallets are the standard European 120x80x14.4 pallets, EUR2 are 120x100 while EUR6 are 80x60. Height is the same for every pallet and from now on will not be reported it anymore. American standards are slightly different (40x48 inches) while in Japan the standard measure is 110x110.
Transportation of chemicals often makes use of pallets with base 120x120 since the squared shape allows a better transportation of circular tanks. Generally, no true standardization exists regarding pallet dimensions and technically they can be customized to cope with shipper's needs. However, in this study we limit our focus only on the most common dimensions available on the market, since the chance of using such kind of pallets is much higher than those with customized dimensions.
Good practices in palletization impose that goods are limited within the pallet boundaries, to allow a better loading of goods on vehicles and improve stability.

Another option is to consolidate packages inside customs crates. Crates can be of different materials (wood, plastic, steel etc) and since are custom made, can have any shape and dimension. The main advantage of crates, when compared to pallets, is that the material is completely protected, thus greatly decreasing the chance of damages to the material. Moreover, if resistant enough, it can be considered as stackable TU (other goods can be loaded upon it) and, if the packaging allows it, it can be considered as turnable too (i.e. length or width can be considered as height), while pallets, on the other side, can possibly be stackable but are never turnable. Stackability is an important aspect to be dealt with when considering how to consolidate multiple loose packages.

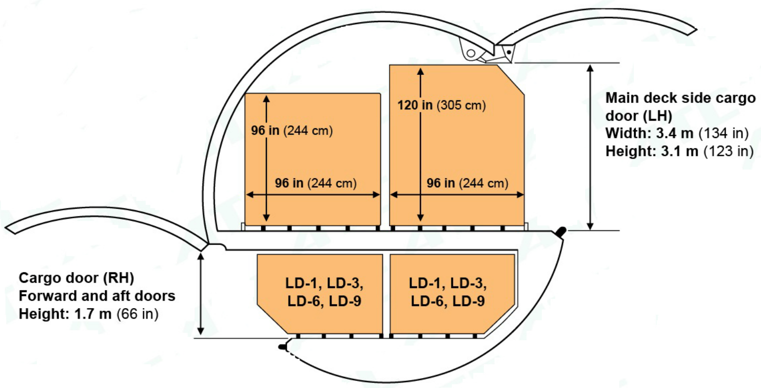
Air transportation services apply a unitary freight on the taxable weight, which is the higher between the real weight of the shipment and the weight equivalent conversion of its volume. Every cubic meter is equal to approximately 167 kilograms of weight. The reason for this conversion rate is that it is one sixth of the standard rate of conversion which is 1,000 kg for every cubic meter (CBM) of volume (this standard conversion is known as *metric tonnage*). When packages/TUs are stackable, the volumetric weight is converted on the actual volume of the package. On the other side, when goods are not stackable, they effectively occupy the volume generated by the projection of the base dimensions to the maximum height of the vehicle.

Each airplane model has different sizes of the cargo hull and, thus, its limitations and characteristics must be considered. Air transportation is carried out by two main families of aircraft: Passengers and Freighter. Passenger aircrafts (PAX) transport passengers on the upper deck and cargo on the lower section of the aircraft. Higher priority is given to passenger's luggages and the remaining slots are allocated to cargo shipments. Depending on the model of the aircraft, different kind of Load Unit (LU) can fit inside the lower deck, defining the constraints in loading the cargo into the plane. The most common internal heights for LU for passenger airplane are 130 and 160 cm for medium and long range flight, while short range flight usually requires smaller airplanes with maximum height on the lower deck of 110 cm. Very small aircraft do not use LUs or any kind of consolidated shipment and only accept loose packages with very limited weight and dimensions.

LUs shape and size defines the maximum dimensions allowed for each TU to be accepted on a given airplane. The TU is limited in every dimension by the physical boundaries of the LU. However, when using standardized TU like pallets, their base is always loadable within any LU, and the only dimension which is limited is the height.

Freighter (Cargo Aircraft Only, or CAO) aircraft do not transport passengers and, thus, can make use of the upper section deck to transport cargo. The upper section deck exploits the circular shape of the aircraft to allow the transportation of bigger packages. Most of the times the upper deck do not use LUs and directly load the consolidated transport unit. One strict condition imposed by air companies is that material to be loaded on the upper deck must be forkliftable and movable with handling vehicles.

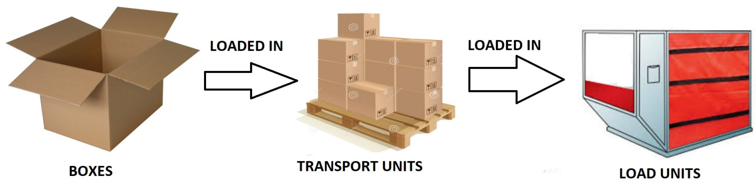
Figure 5.1: Cross-section



In figure 5.1 a cross section of a CAO aircraft is shown. The lower part is the lower deck and it is loaded with LU only (LD-1 and LD-3 are the most common types of LUs). Upper deck is loaded with both LU and loose packages, especially if their dimensions are out of the gouge for the LU. The upper deck height limit depend on the base dimension of the package: with a small base it can be placed near the center where the shape of the aircraft allows for a higher height, otherwise, the wider the base, the lower is the maximum height allowed. For aircrafts with a side door the height of the door is usually considered as maximum height allowed for transport. CAO aircrafts have a maximum loading height for cargo of 290 cm for medium sized aircraft and 310-320 for large sized aircraft. Even bigger CAO aircraft exists but do not operate with a line service and rely purely on chartering and thus are not considered in this work.

In this paper we study the problem of consolidating loose packages (boxes) in TU to be transported through air transportation services. As shown in Figure 5.2, we want to consolidate boxes into pallets, pallets are themself then loaded into LUs by the air company (or by a third party logistics company appointed by the air company). The study ignores the LUs loading problem since it is carried out by air companies and have particular challenges, widely depicted in Paquay et al. (2018).

Figure 5.2: Boxes, transport units and load units



The Air Transport Unit Consolidation Problem (ATUCP) is thus the problem where, given a set of loose packages, the best packing into TUs has to be determined in order to minimize the total cost

Based on the definition given in Bortfeldt and Wäscher (2013) the ATUCP can be considered as a Multiple Bin-Size Bin Packing Problem (MBSBPP) since the boxes to be packed are extremely heterogeneous, while pallets are weakly heterogeneous. We want to consolidate a set of boxes into the optimal heterogeneous mix of TUs of any given type that seeks the minimization of an objective function considering the value of the TUs (i.e. their taxable weight) and the position of the center of gravity. As explained later, the taxable weight is the unit of measure to which the unitary freight is applied by air companies. Clearly, it cannot be lower than the sum of the weights of the boxes. When weight is low though, the volumetric weight conversion is usually higher and thus a proper consolidating technique is needed to effectively reduce the cost of the shipment.

Boxes can be stackable or non stackable, in the latter case no other boxes can occupy the space upon the non stackable box. Moreover, boxes can or cannot be turnable, i.e. two dimensions can be swapped. It is assumed that base dimensions are always swappable, the length can become the width and vice versa. This is not always the case if other means of transportation are considered (for instance, if we consider the consolidation of goods to be shipped through containerization, a package can have extraordinary dimensions that allow it to be forkliftable only on one side, and thus it can be loaded only with the dimensions derived by the given rotation).

One aspect to be taken into account when planning the load layout of a TU is the position of the center of gravity of the load. The center of gravity is the unique point where the weighted relative position of the distributed mass sums to zero. Assuming that the weight is always equally distributed, every box have its center of gravity equal to its geometrical center, and the center of gravity of the TU will be the weighted average point of the boxes' center of gravity. A well balanced TU, with a center of gravity placed near the central point of the base, is easier to transport when lifted with forklifts or cranes, is more stable due to a better balance and, especially when pallets are considered, is more resistant and less subject to damages to the base. Usually it is better to keep heavy items at the bottom of the TU in order to avoid damages to other boxes and improve the balance of the cargo when subject to horizontal movimentation. Therefore, one of the objective we seek is to place the center of gravity as near as possible to the center of the base and in the lowest position possible. Thus, the objective of the ATUCP combines the minimization of total costs and the optimization of the center of gravity. In the next section, we show a numerical example of cost calculation.

5.1.1 Example of cost calculation

Consider the following simple example of cost calculation: we need to transport 12 boxes with dimensions 60x40x60 and we have availability of pallets with base 120x80. Assume also that the weight of boxes is very limited and therefore only the volume is considered as limit. We can choose to consolidate the boxes in one single pallet 120x80x195 (solution 1) or two pallets where one has dimensions 120x80x135 and the other has dimensions 120x80x75 (solution 2).
The following table 5.1 reports the volumetric weight for the two possible consolidation options, considering the consolidated transport unit as non stackable. Stackability is a characteristics of both boxes and TUs. When a TU contains non stackable boxes, it usually is non stackable. In the following example and in the problems studied, TUs are never stackable. Whenever a TU is non stackable, the volume is calculated applying the maximum height of the LU/airplane deck, usually this maximum is considered using a standard height of 160 cm for lower deck cargo and 290 cm for upper deck cargo.

Table 5.1: Weights

	Volume Convertion
Solution 1	464 kg
Solution 2	513 kg

Consolidating in one pallet generates less volume (since it is not stackable $120 \cdot 80 \cdot 290 = 2.784$ CBM$\cdot 167 = 464$ kg), but forces to fly with a freighter aircraft since its height is greater than the maximum height of the LU (160 cm). Pallets with lower height on the other side generates more taxable weight ($120 \cdot 80 \cdot 160 \cdot 2 = 3.072$ CBM $\cdot 167 = 513$ kg). Freighters usually presents lower frequency and higher rates. For instance, if a PAX company offers a freight of € 2.00/kg and a CAO company offers a freight of € 2.30/kg, the total freight paid is as per table 5.2 below.

Table 5.2: Costs

	Total Cost
Solution 1	€ 1,067.00
Solution 2	€ 1,026.00

In this case creating two pallets is the smartest option, since it reduces the total cost of the air shipment. Furthermore, if we consider the availability of pallets with base 120x120 we can consolidate all the boxes on a single pallet 120x120x135 with a volume weight conversion equal to 384 kg. Considering the freight of PAX flight € 2.00 the cost is € 768.00 for a non stackable pallet. Consolidating the boxes in a single pallet with base 120x120 is at this point the best option.

5.2 Literature

The ATUCP is a three dimensional bin packing problem (3D-BPP) where the objective is finding the optimal way to allocate loose packages to TU in order to seek the minimization of TU's cost function and optimize the center of gravity. Martello et al. (2000) gives a description of the 3D-BPP and propose an exact branch and bound algorithm for the solution of large instances. Other mathematical models implementing a wide range of constraints, reflecting operational needs rising in logistics operators, are solved with exact methods in Alonso et al. (2019). A MILP formulation with different valid inequalities is presented by Hifi et al. (2010) while approximation algorithms are proposed in Miyazawa and Wakabayashi (2009). 3D-BPPs are often very difficult to solve with exact methods. Henceforth, a wide range of heuristics approaches has been introduced in the literature. Tabu search techniques are presented in Lodi et al. (2002) and Crainic et al. (2009) with good results. Gendreau et al. (2006) propose a tabu search algorithm capable of solving a combined capacitated vehicle routing problem. Genetic algorithms proved to be very successful in solving the 3D-BPP, examples can be found in Kang et al. (2012), Wu et al. (2010), Gonçalves and Resende (2013) and Ha et al. (2017).
None of the paper mentioned above tackle the ATUCP. Thus, we now provide a formal description of the problem.

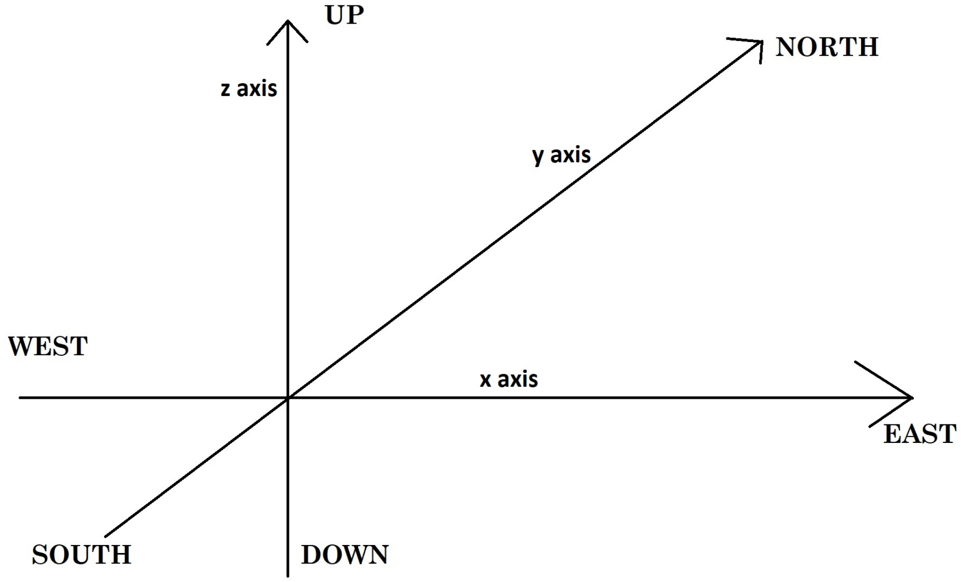
5.3 Problem Description

In this section we formally describe the problem. We start by defining the parameters and then present the formal definition of the problem.

5.3.1 Problem setting

We consider the XY plane as a geographical map, so we move along the X axis from west to east, and along the Y axis from south to north. Z axis start from the down position and ascend towards the up position. Figure 5.3 shows a representation of the coordinate system used.

Figure 5.3: Coordinate system



Each box $b \in B$ where B is the set of the boxes to be consolidated in TUs is defined by the following parameters and properties:

- x_b: The measure of the box's width.
- y_b: The measure of the box's length.
- z_b: The measure of the box's height.
- w_b: The box weight.
- st_b: Boolean value indicating if a box is stackable. If a box is non stackable, no boxes can lay upon it.

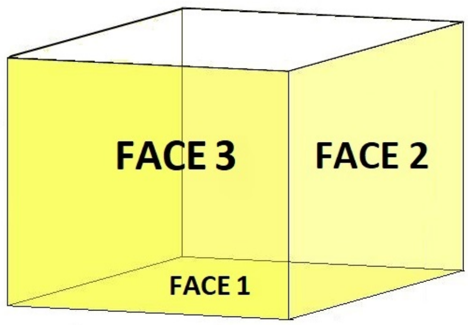
- TXZ_b: Boolean value indicating if a box can be turned in order to let its face defined by the XZ plane to be the base (i.e. if according to figure 5.4 the box can use Face 3 as a base)

- TYZ_b: Boolean value indicating if a box can be turned in order to let its face defined by the YZ plane to be the base (i.e. if according to figure 5.4 the box can use Face 2 as a base)

- CG_b: Center of gravity of the box. It corresponds to a point and it is determined by its coordinates $x_{CG_b}, y_{CG_b}, z_{CG_b}$

All boxes uses Face 1 as their base, as depicted in figure 5.4.

Figure 5.4: Box faces



Furthermore it is assumed that it is always possible to swap the current dimensions of x_b and y_b whatever is the face used as base.
TUs $tu \in TUS$, where TUS is the set of existing type of TUs, are associated with the following parameters:

- x_{tu}: The TU's width.

- y_{tu}: The TU's length.

- z_{tu}: The TU's height.

- Q_{tu}: The maximum weight that can be carried by the TU.

- CG_{tu}: Center of gravity of the TU. It corresponds to a point and it is determined by its coordinates $x_{CG_{tu}}, y_{CG_{tu}}, z_{CG_{tu}}$.

5.3.2 Problem formalization

The objective of the ATUCP is to find the optimal consolidation layout of all boxes in B which minimize the value of objective function (5.1), which we call *fitness*.

$$FITNESS = \sum_{tu \in TUL} TW_{tu} + \alpha \cdot CGV_{tu} \tag{5.1}$$

In which TUL is the set of TUs chosen in the solution and:

- $\sum_{tu \in TUL} TW_{tu}$ is the sum of the taxable weight of all the TUs chosen. The taxable weight is directly related to the total cost of the shipment.

- $\sum_{tu \in TUL} CGV_{tu}$ is the value given to the position of the center of gravity of each $TU \in TUL$. Parameter α is the weight given to this objective.
  We define the center of gravity of the TU (CG_{tu}) as the average position of the centers of gravity of the boxes inside the TU weighted for their weight. The X coordinate of CG_{tu} is calculated as $\frac{1}{\sum_{b \in tu} w_b} \cdot \sum_{b \in tu} x_b \cdot w_b$. Y and Z coordinates are calculated in the similar way. Only the position of CG_{tu} is checked and not its weight concentration.
  We define as C the point representing the center of the base of the TU. CGV_{tu} is calculated as the euclidean distance between the projection of CG_{tu} on the base of the TU (XY plane) and C, multiplied for $\frac{z_{CG_{tu}}}{z_{tu}}$. The more CG_{tu} is centered and in lower position, the lower is the value of CGV_{tu}.

The feasible solution space is defined by the following set of constraints:

- Weight limit: For every TU, the sum of the weights of the boxes loaded must be lower than the TU weight capacity Q_{tu}.

- Box stackability: Not every box is stackable. The space above non stackable boxes must be left free.

- Box orientation: Not every orientation is allowed for boxes.

- The boxes must be within the TU's boundaries.

- No boxes can overlap, i.e. one box cannot penetrate within another box.

Note that these constraints do not consider vertical stability. The usual approach to ensure vertical stability is to fill the eventual empty spaces with pluriball / alluminium sheets. The proposed packing procedure focuses on trying to limit as most as possible the creation of gaps and empty spaces and henceforth no hard constraints are implemented to ensure vertical stability. To the author's knowledge, there is no version of MBSBPP considering this set of constraints in the literature.

5.4 Solution algorithm

The general scheme of the algorithm is the following. We start by selecting one type of LU that will be used. It is assumed that the base dimension of TUs are always within the boundaries of the LU, therefore the height is the only effectively limited dimension. Moreover, we select one type of TU and apply the 3DBP-Algorithm to it as showed in Section 5.4.1. From the starting solution it is applied a first order local (1LS) search to check if a better solution can be found and, if that is the case, the incumbent solution is updated. We proceed with 1LS until no improvements are found and then, from the incumbent solution, a second order local search (2LS) starts by removing one TU from the incumbent and using the 3DBP algorithm on the boxes previously contained in the removed TU, using a different type of TU. Every time we find a new solution through a 2LS we pass it to 1LS. We apply 2LS until any possible combination of allowable TUs is checked. We repeat the procedure for LUs of different maximum heights. The scheme is depicted in Figure 5.5.

5.4.1 3DBP-Algorithm

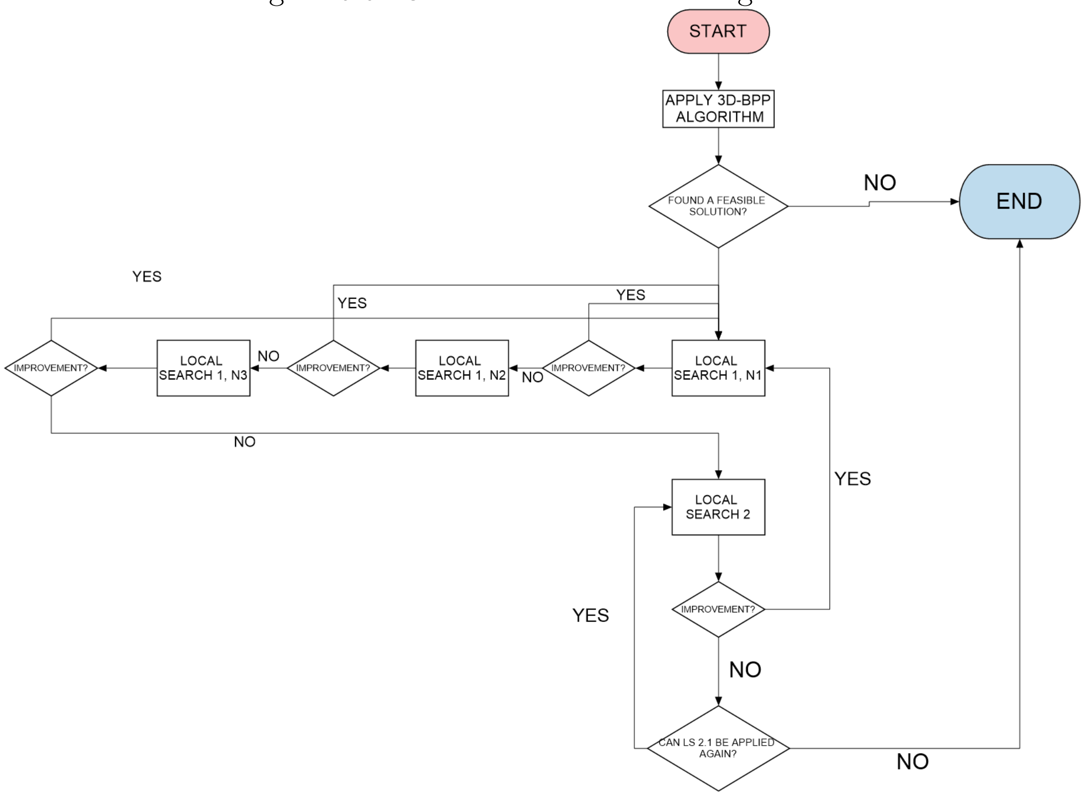
It is used an adaptation of the Extreme Point (EP) methodology introduced by Crainic et al. (2008). The scheme of the 3DBP-Algorithm is depicted in Figure 5.7. The algorithm works as follows.

Given the set B of boxes to be packed and one type of TU, the algorithm is initialized by creating one TU, $TU1$, with dimensions (x_{TU}, y_{TU}, z_{TU}) and weight capacity (Q_{TU}) and add it to TUL. Then, the algorithm sort the set of boxes B using the $SORT(n, m, TU)$ algorithm described in section 5.4.1, to identify the order in which boxes are inserted.

Ideally, big boxes should be inserted first to occupy as much space as possible, while the remaining empty space will be filled by smaller packages. Moreover, heavier boxes needs to be placed at the base of the TU.

Once the list of boxes to be packed B is properly sorted, the packing process begins. The algorithm make use of Extreme Points and every EP e is defined by the following

Figure 5.5: General scheme of the algorithm



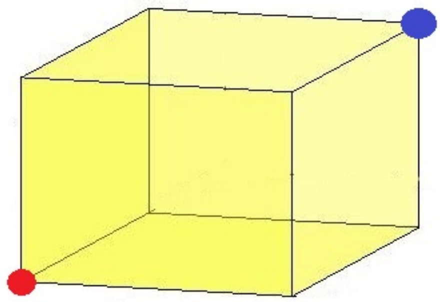
characteristics:

- x_e: EP's position along the X axis.
- y_e: EP's position along the Y axis.
- z_e: EP's position along the Z axis.
- MX_e: Maximum dimension allowed along the X axis for a box to be positioned in EP (i.e. the maximum width a box placed in EP can have). It is calculated as $MX_e = x_{tu} - x_e$ if no boxes are placed between the EP and the TU eastern boundary, otherwise $MX_e = x_{e1} - x_e$ where $e1$ is the EP where the box placed between the EP and the TU eastern boundary is placed.
- MY_e: Maximum dimension allowed along the Y axis for a box to be positioned in EP (i.e. the maximum length a box placed in EP can have). It is calculated as $MY_e = y_{tu} - y_e$ if no boxes are placed between the EP and the TU northern boundary, otherwise $MY_e = y_{e1} - y_e$ where $e1$ is the EP where the box placed between the EP and the TU northern boundary is placed.
- MZ_e: Maximum dimension allowed along the Z axis for a box to be positioned in EP (i.e. the maximum height a box placed in EP can have). It is calculated

as $MZ_e = z_{tu} - z_e$ if no boxes are placed between the EP and the TU upper boundary, otherwise $MZ_e = z_{e1} - z_e$ where $e1$ is the EP where the box placed between the EP and the TU upper boundary is placed.

We define the list of EPs available in the TU as EPL and we add the EP (0,0,0), the origin of coordinates, to EPL_{TU_1}. We use the system of coordinates depicted in Figure 5.3. Whenever we create a TU, the first EP available (0,0,0) is the south western down corner of the TU. Similarly, we position the south western down corner of a box on EPs.
We take the first box on the list B and, if it fits, insert it in the only EP available in EPL_{TU_1}, (0,0,0). We then update the list of available EPs in the TU by using the EP Generation Algorithm depicted in Section 5.4.1.
The following box is then selected to be packed. For every EP in the list EPL of every TU created we check, for every orientation allowed, if the box can be inserted in the position given by the EP. This check is performed by the CanFit Algorithm described in Section 5.4.1. Briefly, for each box its position is identified by defining the south west down corner (the one touching the EP, red in figure 5.6) and the north east up corner (blue in figure 5.6), and it is controlled if boxes overlaps by checking the coordinates of said points. If the box can be placed, the EP is priced

Figure 5.6: Corners considered to check in boxes overlaps



with the best orientation possible according to the following cost formula

$$COST(b, e, N) = 2N \cdot z_e + x_e + y_e + N \cdot (z_e + z_b) + \theta \cdot N \cdot (MX_e - x_b) + \theta \cdot N \cdot (MY_e - y_b) \tag{5.2}$$

where $b \in B$ is the box, $e \in EPL$ is the EP, N is a big integer positive number and:

- $2N \cdot z_e + x_e + y_e$ is the position of the EP where the box will be placed. Western, southern and lower EPs are preferred.
- $N \cdot (z_e + z_b)$ is the height coordinate of the western, southern, upper corner of the box. It represents the height of the box within the TU and favors orientations that minimizes the height

- $\theta \cdot N \cdot (MX_e - x_b)$ represents how effectively the box occupy the remaining space left for the EP along the X axis.
- $\theta \cdot N \cdot (MY_e - y_b)$ represents how effectively the box occupy the remaining space left for the EP along the Y axis.

The idea of the pricing formula is to prefer the southern western down available EP, while taking into account both the height of the box (in order to favor orientations where the height of the package is lower) and the remaining space available after a box has been inserted, to better occupy the empty space of the TU. We check if a box can fit in every EP in each created TU for every orientation allowed by the box, calculate its cost and select the one which has the overall minimum cost. The box is inserted in the selected TU at the selected EP and:

- The list of available EPs is updated using the EP Generation Algorithm, adding the potential new points to EPL.
- The maximum dimensions of every EP of the TU are updated.

If otherwise no suitable EP exists, a new TU is created and the box is added in the only available EP, (0,0,0). The inserted package is then removed from B, and the algorithm iterate until every box is added to one TU.

Sorting Algorithm

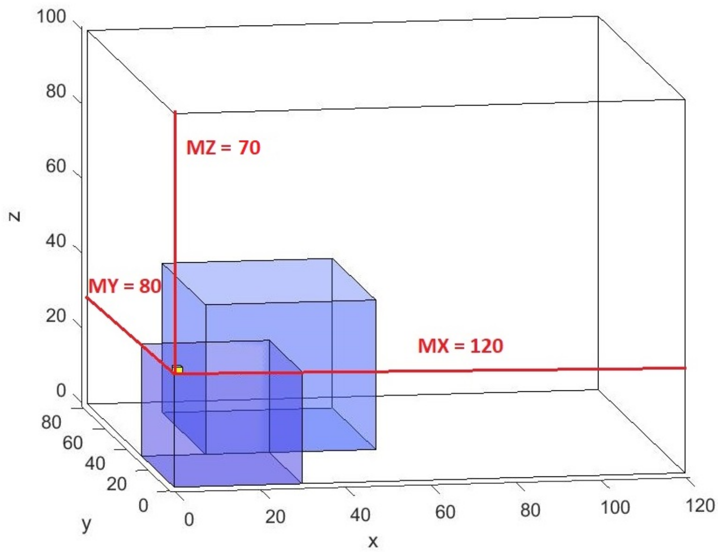
Since the goal is to build TUs with the lower height possible, the sorting algorithm $SORT(n, m, TU)$ at first rotate each box, if it is allowed, in order to have the minimum possible height.
The algorithm then divide the set B in n clusters of first order, based on the packages weight. It furthermore divide each first order cluster in m second order clusters based on the dimension of the base. Lastly, each of the $n \cdot m$ clusters is ordered considering the height of the boxes and the set B is reassembled.
For the first order clustering, if the weight of box $b \in B$ $wgt_b \in (Q_{TU} \cdot \frac{i-1}{n}, Q_{TU} \cdot \frac{i}{n}]$ then the package is inserted in the cluster of first order $C(i)$. For the second order clustering, if $(x_b \cdot y_b) \in (x_{TU} \cdot y_{TU} \frac{j-1}{m}, x_{TU} \cdot y_{TU} \frac{j}{m}]$ then the box is inserted in the cluster of second order $C(i, j)$. As a third level ordering, every cluster of second order $C(i, j)$ is internally sorted on the basis of the height of the boxes, with the higher boxes moved at the beginning of the list. Finally, all clusters $C(i, j)$ are taken in decreasing order (from $i = n$ and from $j = m$) and the boxes contained in

the cluster are added to the ordered list of boxes B. This way, B is sorted according to weight first, base dimensions second and height last.

CanFit Algorithm

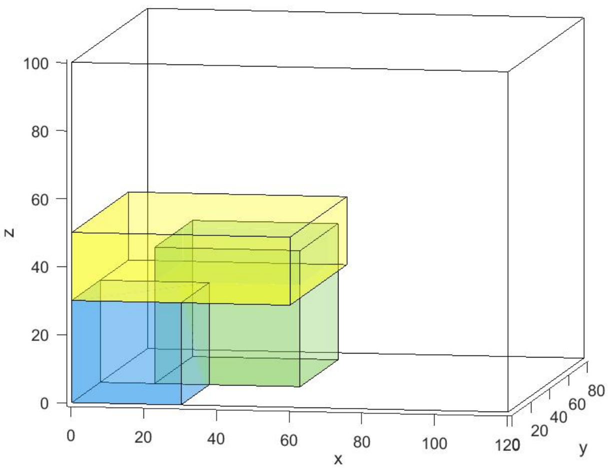
Two checks are made to determine whether boxes overlap. First, it is verified if the box $b1$ dimensions are lower than the maximum dimensions allowed for a package in the EP *ep*. This first check is unable to recognize every situation in which boxes overlap. Consider the following example. In a pallet 120x80x100 we have, among the others, one box b_1 30x30x30 in position (0,0,0) and another box b_2 40x40x40 in position (15,30,0). If we consider EP (0,0,30), the one generated by the south west up corner of the first box, we can easily check that there are no boxes along its projections and so the maximum dimensions for boxes considered for that EP are 120 along the X axis, 80 along the Y axis and 70 along the Z axis, as showed in figure 5.8.

Figure 5.8: Boxes placed in the pallet and maximum dimensions for EP (0,0,30)



Next, we want to insert a box b_3 60x60x20. By applying the first fit check mentioned above, we should be able to insert it in (0,0,30) since the dimensions of the box are lower than the maximum dimensions of the EP. Figure 5.9 shows the result of this operation

Figure 5.9: Overlapping box



Clearly boxes b_2 and b_3 overlaps. Henceforth, we need a further check based on the position and dimensions of the other boxes already placed in the TU. For the sake of readability we make use of the following notation. Given a box b we identify:

- x_b^{RED} is the coordinate along the X axis of the southern western down corner of the box (red point in Figure 5.6).
- y_b^{RED} is the coordinate along the Y axis of the southern western down corner of the box (red point in Figure 5.6).
- z_b^{RED} is the coordinate along the Z axis of the southern western down corner of the box (red point in Figure 5.6).
- x_b^{BLUE} is the coordinate along the X axis of the northern eastern up corner of the box (blue point in Figure 5.6). It is equal to $x_b^{RED} + x_b$.
- y_b^{BLUE} is the coordinate along the Y axis of the northern eastern up corner of the box (blue point in Figure 5.6). It is equal to $y_b^{RED} + y_b$.
- z_b^{BLUE} is the coordinate along the Z axis of the northern eastern up corner of the box (blue point in Figure 5.6). It is equal to $z_b^{RED} + z_b$.

Boxes are placed with their red corner in EPs. To check if box $b1$ to be placed in EP e overlaps box $b2$ we check if the following condition is true.

$$\max(x_{b1}^{RED}, x_{b2}^{RED}) < \min(x_{b1}^{BLUE}, x_{b1}^{BLUE}) \ \wedge \ \max(y_{b1}^{RED}, y_{b2}^{RED}) < \min(y_{b1}^{BLUE}, y_{b1}^{BLUE}) \\ \wedge \ \max(z_{b1}^{RED}, z_{b2}^{RED}) < \min(z_{b1}^{BLUE}, z_{b1}^{BLUE}) \tag{5.3}$$

If (5.3) holds than there is overlap between boxes and therefore the box b cannot be placed in that EP.

EP Generation Algorithm

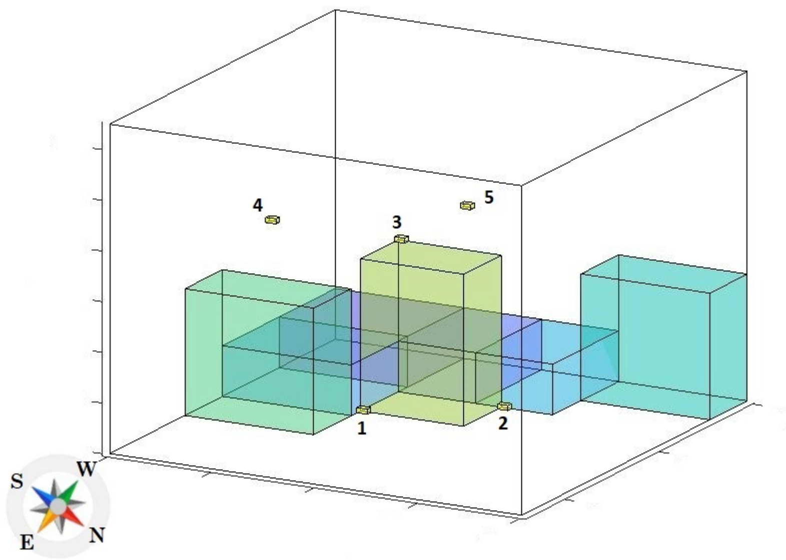
Each time a box is added to a TU, the algorithm removes the EP where the box is placed from EPL. Then, the algorithm adds up to five new EPs. Given the EP e as the EP where the box b is placed, the generation of new EPs is the following:

1. The point (x_e + x_b, y_e, z_e) (i.e. the south east down corner of package b) is projected *down*, until it touches the base of the TU in the XY plane or the up face of a box. The resulting point is then projected south, until it touches the plane XZ or the north face of a box. The point resulting from the projection is added to EPL_{TU_1}. More precisely, the projection down either touches the plane at point (x_e + x_b, y_e, 0) or it stops on the face of the first package $b1$ it encounter in point (x_e + x_b, y_e, $z_{e1} + z_{b1}$) where $e1$ is the EP where package $b1$ is placed. The algorithm proceeds to project the newly found point to the ZX plane until it touches the plane in either point (x_e + x_b,0,0) or point (x_e + x_b, 0, $z_{e1} + z_{b1}$), or until it touches the face of the first package $b2$ along the projection in either point (x_e + x_b, $y_{e2} + y_{b2}$, 0) or point (x_e + x_b, $y_{e2} + y_{b2}$, $z_{e1} + z_{b1}$), depending on the previous projection. The point found is added to EPL_{TU_1}
2. The algorithm project point (x_e, y_e + y_b, z_e) (i.e. the north western down corner of package b) in the same way we projected point 1) first on the XY plane and then to the YZ plane.
3. If st_b = TRUE, the algorithm take point (x_e, y_e, z_e + z_b) (i.e. the south western up corner of package b) and add it to EPL_{TU_1}.
4. If st_b = TRUE, the algorithm take point (x_e, y_e, $z_e + z_b$) (i.e. the south west up corner of package b) and project it to the ZX plane until it either touch the plane in point (x_e, 0, $z_e + z_b$) or it stops the projection on the face of the first package encountered $b1$ in point (x_e, y_{e1} + l_{b1}, z_e + z_b). The point resulting from the projection is added to EPL_{TU_1}.
5. Similarly to 4), point (x_e, y_e, z_e + z_b) is projected to the ZY plane if the package is stackable. The projected point is added to EPL_{TU_1}.

It is to be noted that when box b is the first box inserted on a newly created TU, the projection of points 1) and 2) are equal to the starting point themselves, (x_e

+ x_b, y_e,z_e) and (x_e, $y_e + y_b$, z_e) respectively. Moreover, point 3) is equivalent to the projection of the point to the plane ZY and ZX, resulting in the generation of 3 points instead of 5.
In figure 5.10 it is showed a graphical example of the depicted procedure, where a newly inserted box generates the five different new EPs.

Figure 5.10: EP generation example



Once the updating phase of EPL_{TU_1} is concluded with the removal of any duplicate of already existing EPs in the list, a box is inserted in a TU and it is removed from B.

5.4.2 1LS

The objective of 1LS search is to improve the solution found by 3DBP without changing TU type. 1LS explore three different neighborhoods:

- N1: In N1 the local search pick one box on top of one TU and move it on top of another TU. Different strategies are used to select box, TU of original position and the TU where to place the box (from the heaviest TU to the less, from the heaviest to another TU randomly selected, from the highest to the lower, from the highest to another TU randomly selected and fully random). The local search tries the same moves with two ore more boxes.
- N2: In N2 the principle is similar to N1 but instead of moving one or more

boxes from one TU to another, the local search select one box in top position from one TU, one box in top position from another TU and swap their positions. These moves are chosen at random and the solutions found by the swapping are kept for a few moves, even if they do not lead to a direct improvement.

- N3: In N3 the local search select two or more TUs at random, destroy them and apply the 3DBP algorithm to rebuild the TUs.

Clearly 1LS can be applied whenever the solution found by the 3DBP algorithm contains at least two TUs (at least three to explore N3 otherwise the solution found will be exactly the same). The local search first explore N1, then N2 and last N3. Whenever the local search finds an improvement in any of the three neighborhoods, it saves the incumbent solution and re-apply 1LS from scratch. If no improvement of the solution is found, the algorithm proceeds to apply 2LS.

5.4.3 2LS

With 2LS some TUs in the incumbent solution are destroyed to be substituted by a different type of TU. The idea is that the currently used TU is not necessarily the best option available. Instead of doing an extensive search by checking any combination available, the algorithm identify the best candidates to be destroyed and rebuilt through the 3DBP algorithm. The candidates are the following:

- Empty TUs: TUs that have a filling percentage lower than a certain amount are not optimized, a smaller TU can potentially be able to contain the same boxes with a lower cost.
  Generally speaking, if the solution include a TU with a very high fill percentage, destroying that TU to rebuild it with a different TU will unlikely lead to an improved solution, therefore the idea is to try to avoid potentially bad moves.

- TUs where the lateral space left is superior to a certain amount. If the minimum space left between the boxes and the boundaries of the TU along the X and Y axis is high, the solution can potentially be improved by selecting a different TU. TUs with a broader base can contain more boxes, potentially reducing the total number of TUs used. On the other side, TUs with a narrow base are used better and their cost is potentially lower.

5.5 Numerical example

It is now presented a brief numerical example to better explain the packing procedure. Figure 5.11(a) shows a partial solution produced by the 3DBP algorithm for a standard Europallet 120x80x130 where we highlight the currently available EPs. In the next iteration we need to insert a box with dimensions 30x40x20, weight is not considered in the example.

Figure 5.11: Boxes and EP in the TU

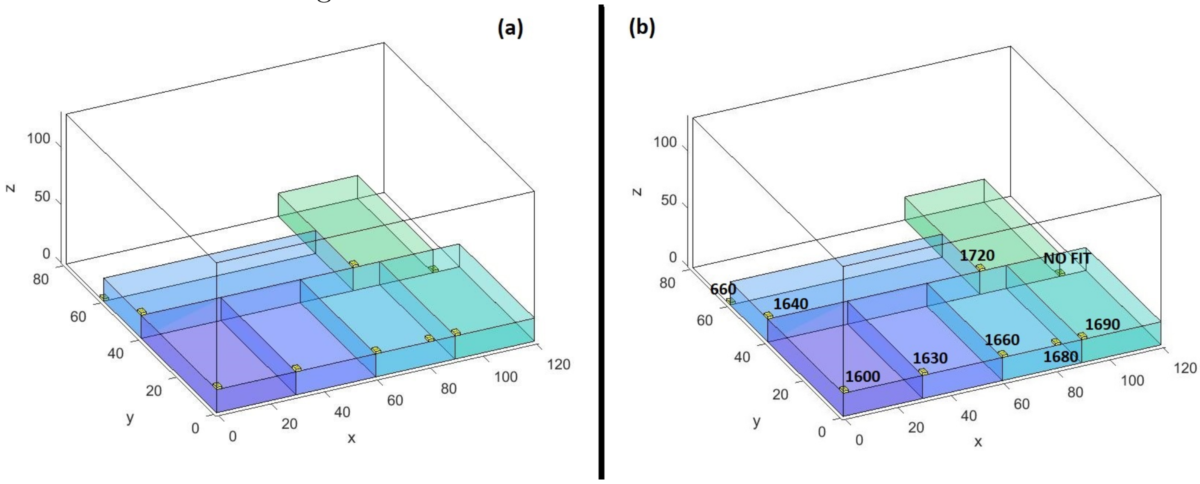


Table 5.3 show the available EPs and the maximum dimensions allowed for a box to be placed at the EP. It can easily be checked that the box can fit in every EP

Table 5.3: EPs coordinates and maximum measures

EP	X_e	Y_e	Z_e	MX_e	MY_e	MZ_e
1	30	0	20	90	80	110
2	60	0	20	60	80	110
3	0	60	0	80	20	130
4	0	0	20	120	80	110
5	90	0	20	30	80	110
6	0	40	20	120	40	110
7	80	0	20	40	80	110
8	80	40	20	40	40	110
9	110	40	0	10	40	130

with the only exception of EP 9, since the box has no dimension lower than 10, the maximum width allowed by the EP. For every EP where the box can fit, the cost of the EP for every available rotation is calculated using $COST(b, e, N)$ and the best rotation is selected. The EP with the minimum cost is then selected. Table

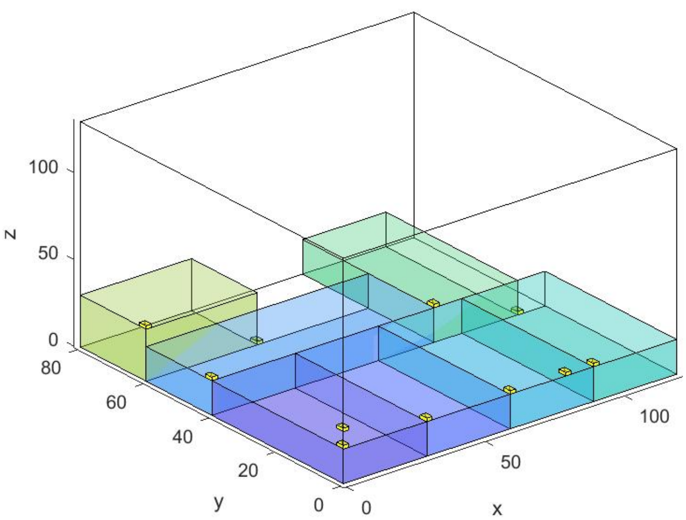
5.4 shows the results of the calculation, represented visually on Figure 5.11(b). For simplicity, we only consider and report the cost of the best orientation for every EP. The goal is to place the box in the lowest, western southern point available.

Table 5.4: EPs coordinates and cost

EP	X_e	Y_e	Z_e	Cost
1	30	0	20	1630
2	60	0	20	1660
3	0	60	0	660
4	0	0	20	1600
5	90	0	20	1690
6	0	40	20	1640
7	80	0	20	1680
8	80	40	20	1720
9	110	40	0	NO FIT

Even by visual inspection it is easy to verify that the best EP is (0,60,0) and the cost function reflects that. It is noticeable the great gap between lower EPs and higher EPs, and that in a situation of equal height, south-western EPs presents lower costs. Figure 5.12 shows the visual rappresentation of the TU once we insert the box in the lower-cost EP. In order to insert the box in the EP (0,60,0) we must rotate it to have dimensions 40x20x30.

Figure 5.12: TU's visual representation after we insert the package



5.6 Preliminary Results

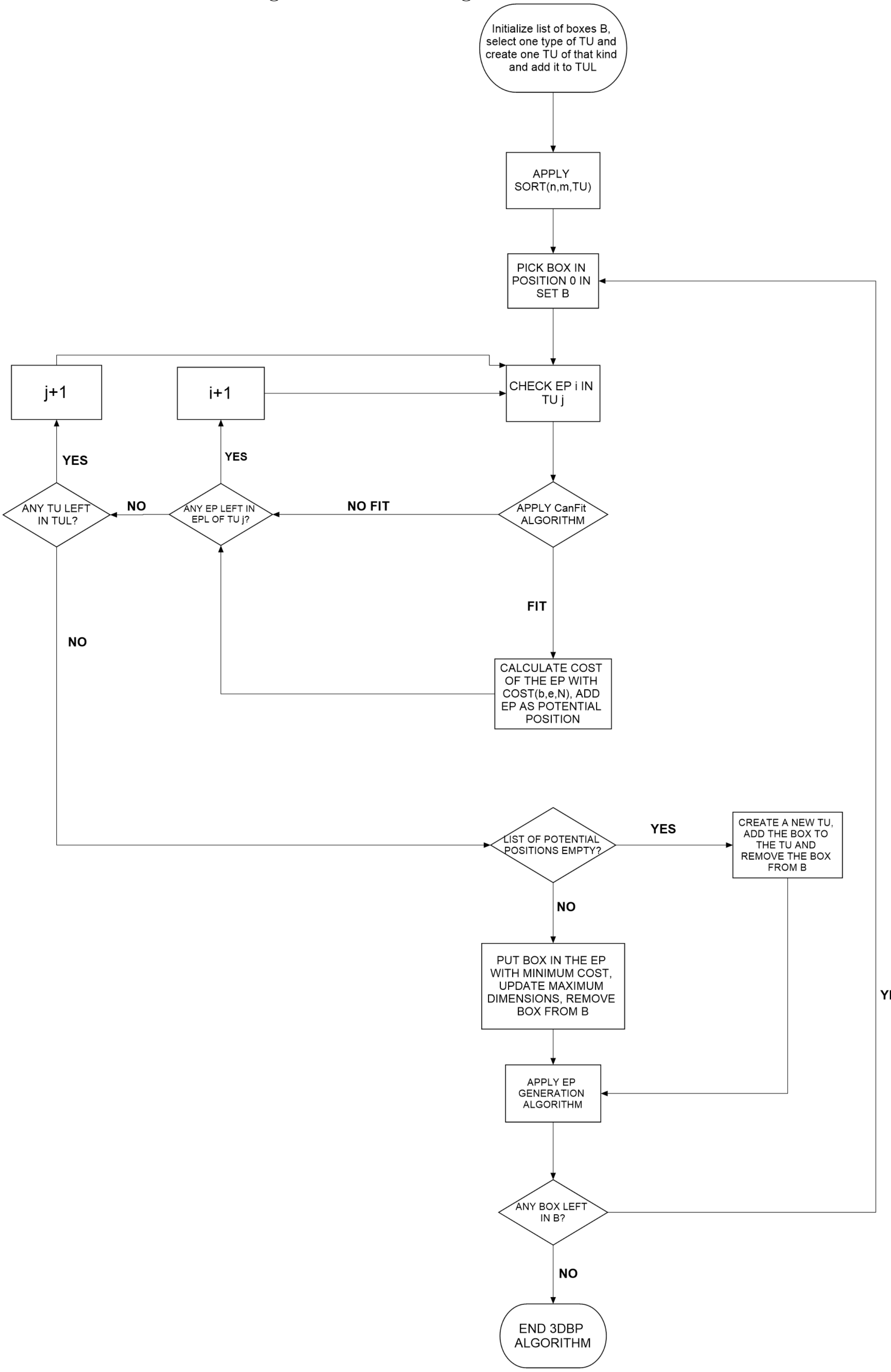
In order to study the behaviour and the effectiveness of the 3D-BPP algorithm, the instances introduced by Bischoff and Ratcliff (1995) are solved. Seven subsets of instances do not consider weight of goods, while 5 subset of instances implement weight in the algorithm. Each subset contain 100 instances and it is defined by the quantity of different kind of boxes considered. For the sake of easing the comparison between the results, in this section the same output reported in Bischoff and Ratcliff (1995) are compared for the first 700 instances (the ones without considering weight). Table 5.5 show the results obtained for each subset of 100 instances solved in terms of: solution time (ST), average utilization rate of fullest container (A%), highest utilization rate of the fullest container (Max%) and the instance which registered the value (MaxI), minimum utilization rate of the fullest container (Min%) and the instance where the value is registered (MinI). When compared to

Table 5.5: Preliminary results

Ist	ST(s)	A%	Max%	MaxI	Min%	MinI
1	10.64	73.39%	85.05%	86	54.75%	18
2	9.24	68.38%	78.09%	40	55.27%	17
3	11.46	66.59%	74.49%	10	54.11%	18
4	10.44	65.44%	73.45%	51	55.12%	19
5	13.12	64.12%	72.74%	34	53.18%	22
6	11.75	62.11%	72.21%	54	51.65%	43
7	12.89	64.77%	75.54%	12	55.87%	18

the results obtained in Bischoff and Ratcliff (1995), the 3D-BPP algorithm seems to perform poorly. The average utilization rate is lower and both maximum and minimum utilization rates are lower. The main reason for this performance issues are to be searched in the logic behind the 3D-BPP proposed and the problem tackled. In Bischoff and Ratcliff (1995) algorithms for container loading problems are presented and their performances studied. Container loading objective is to maximize the utilization rate of the single container loaded, while in ATUCP the objective is different and considers multiple aspects of air transportation. Once the algorithm proposed in this chapter recognize that a certain box cannot be loaded in the existing TU, it proceed to create a new one. At that point, the extreme points in the new TU are more likely to be the convenient choice for successive boxes to be inserted (since they most probably are in southern western lower position with respect to the ones present in the more packed TU) and the algorithm proceed to fill the new TU, balancing the load between the two (or more) existing TU. Overall, though, the 3D-BPP algorithm finds compact and good solutions. Utilization rate is satisfying and boxes are stable and few empty spaces are left between packed boxes. Further improvements in the solution found are expected to be identified by the local searches proposed. The experimental campaign is still a work in progress and further tests will be made to improve the effectiveness of the algorithm presented.

Figure 5.7: 3DBP algorithm scheme



Chapter 6

Conclusions and future research directions

The purpose of this PhD thesis is to develop operational research instruments in order to tackle operational problems encountered daily by freight forwarding companies. To do so, the ATFFSP is introduced into the literature. A MILP formulation based on a time-space network structure is given, and instances generated using real world data are solved. The solutions found by the model are studied and compared with the ones adopted by the freight forwarding company that made the data available. Solutions provide a sensible reduction of costs and the model is capable of finding fast and reliable solutions, usable in real world. The model is also used by the company to get managerial insights regarding the evaluation of the convenience of opening a second warehouse. Overall, the results show the effectiveness of commercial linear programming solvers to find the optimal solution for small and medium scale instances. For large-size instances, however, the number of instances solved to optimality is null, even while the optimality gaps are limited. A sensitivity analysis is carried out in order to identify which characteristics of the model contributes the most to the complexity of the model. The number of variables and constraints impacts minimally on the complexity of the problem, while the number of different shipments that can be consolidated together appears to be a much more influencing parameter. The higher the number of shipments and combinations available for consolidation, the more difficult to solve will the problem be.
In order to solve the difficulties encountered in solving larger instances, a matheuristic approach is presented in the fourth chapter of the thesis. The strategy is to identify feasible routes from origin to destination for every shipment. The solution is then found by solving a set-partitioning formulation. At first, all feasible routes

are generated through complete enumeration. This approach, though, generates a number of routes which is too high to be solved by the commercial solver using the set-partitioning formulation. Henceforth, the first technique developed to reduce the number of routes identified is the implementation of dominance rules, which are applied before, during and after the routing generation process. Despite proving the effectiveness of the proposed dominance rules, with an the average reduction in the number of routes generated of approximately 70%, their use alone is not sufficient to improve the model performances enough in order to be competitive with the MILP formulation. A second approach is developed by identifying multiple services with similar characteristics and then shrinking them by constructing a single virtual service that represents the Pareto frontier of the services shrinked. This so called min-cost frontier technique is proved to be useful when there is a high number of services showing similar characteristics. Finally, a heuristics approach, based on general rules applied by the freight forwarding company that inspired this thesis, is developed. During the routing generation algorithm, only a limited number of services are selected, which must be contained in a given time span. The results for different values of the time span are analyzed, three with a fixed value and three where this value varies according to the transit time requested by the shipment. The results shows the effectiveness of such an approach, with improvements in solution time and solution quality on large instances. Optimality gaps for medium and small size instances are limited and solutions are found in reduced times.
In the last chapter, a three dimensional bin packing problem is presented. The objective is to identify the optimal layout for consolidating loose packages into transportation units in order to be transported by means of air transportation services. The best solution is explored by using a TU constructing algorithm embedded in a two-level local search. Preliminary performance results solving instances well known by the literature are presented.

This thesis introduced in the literature the AFTTSP, an operational problem tackled daily by freight forwarding companies. Multiple operational aspects are not considered and the usefulness of the model presented can be further enhanced by implementing, among the others, constraints on the availability of service used depending on the characteristics of the shipment or additional shipment requirements (e.g. dangerous goods or temperature controlled material).
Heuristic approaches for this problem are limited to the matheuristics presented in the thesis. Further studies can be applied to the development of heuristic and metaheuristics approaches. A column generation technique seems to be the natural evolution of the matheuristics applied and thus should be explored in the future.
Consolidation of loose packages in TUs in a suitable layout for air transportation

is a rarely studied problem. More operational aspects with respect to the ones considered in this thesis can be implemented in order to improve the usefulness of the algorithm proposed.

The problems tackled in this work are just a part of the plethora of challenges encountered by freight forwarder, who has been mostly ignored by the literature and hold potential for useful and interesting studies. Further researches in the field are recommended due to the wide range of problems that still needs optimization techniques as decision support tools.

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