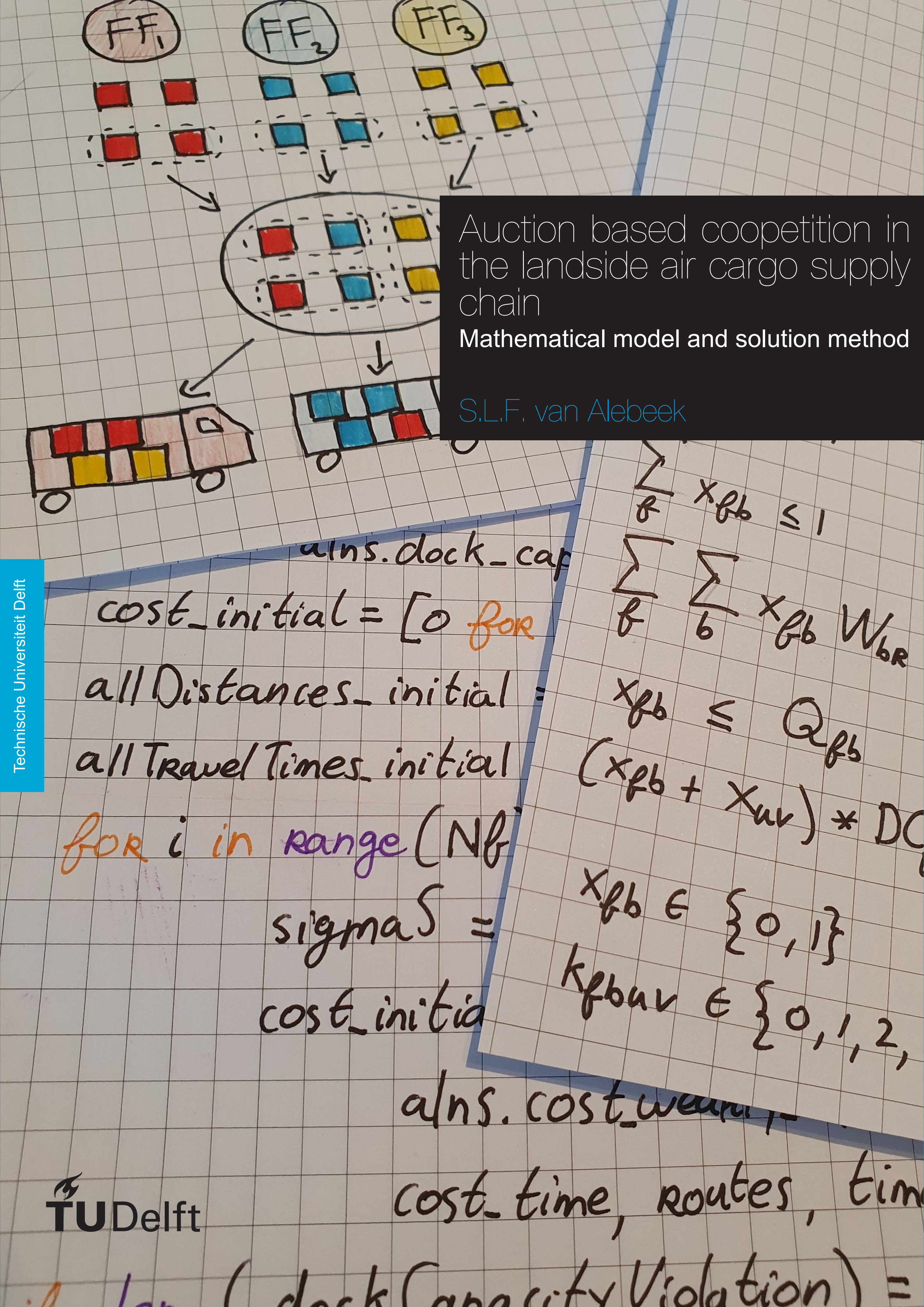

Auction based coopetition in the landside air cargo supply chain

Mathematical model and solution method

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Technische Universiteit Delft

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by

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Preface

”Exact! Precies!” were the famous words of my maths teacher in high school after he gave me a 9.9 for a test. In his opinion my minus sign looked like a dot. Surprisingly, this was also were I got interested in the mysterious and pleasantly organised world of mathematics. This interest also played a role in finding a subject for my Master thesis. After looking for quite a while I found the perfect opportunity to use mathematics in a practical situation: modelling collaboration in the air cargo supply chain. This thesis is my final product for the master Transport, Infrastructure and Logistics at the Delft University of Technology. I hope you will enjoy the read.

Hereby, I want to express my sincere appreciation to my supervisors Prof. dr. ir. Lóránt Tavasszy, dr. Jafar Rezaei, dr. Bilge Atasoy and dr. Alessandro Bombelli. Thank you Lóri for helping me find such a great graduation subject, Jafar for improving my academic way of working, Bilge for our informative meetings that felt like friendly chats, and Alessandro for making it feel like we were in this together.

I would also like to thank my friends for their continued support and for keeping me motivated during this project. Thank you Annemijn, Jordi and Rogier for your excellent feedback and for always being available to answer my questions. Thank you, Marlies, Jasmijn and Laurelle for not letting me forget how to have fun.

Finally, I would like to thank my family and Hugo for all their love and support and at times much needed relaxation. My parents and brother deserve a special thank you for always believing in me from start to finish. Hugo, thank you for giving me that extra push during some of the difficult days and for all the fun besides the hard work.

S.L.F. van Alebeek
Delft, June 12, 2020

Summary

The air cargo transport industry is a highly competitive and complex market. In the air cargo supply chain freight forwarders organise the transportation of requests from shippers. The freight forwarders find a routing strategy for their trucks from the freight forwarding depot to the ground handlers on the airport. Due to the development towards more integrated logistic service providers the complexity and competitiveness for all levels of the supply chain have increased. Until now, freight forwarding companies were able to manage the complexity and competitiveness of the market with high margins, optimisation of their own resources and vertical collaboration. The emergence of integrative services, increased competitiveness with other transport systems and declining operations margins have motivated the freight forwarders in the air cargo transport industry to look into horizontal collaboration. Horizontal collaboration occurs when companies that work at the same level of the supply chain decide to work together, rather than operate separately, with the goal to increase their efficiency.

The main goal of this project is to show the key effects of introducing auction based coopetition, a form of horizontal collaboration where competition is preserved, for the freight forwarders in the landside air cargo supply chain. To show these key effects, a comparison is made between three different types of freight forwarder collaboration: individual planning, full collaboration and the auction based coopetition. In the individual planning each freight forwarder finds the best routing for their own requests individually. In the full collaboration the central planner has full information on the requests of every freight forwarder in the coalition. Therefore, the problem can be seen as if the central planner is one large freight forwarder that needs to transport all requests of the coalition. This is modelled by using a neutral fleet of trucks belonging to all (or no) freight forwarders. The central planner assigns all requests to trucks in such a way that routing costs are minimised.

In the auction coopetition, the focus of this thesis, a framework is followed to redistribute the requests among the freight forwarders:

1. Request selection by the freight forwarders: Every freight forwarder selects requests based on predetermined characteristics to enter in the auction pool.
2. Request bundling by the central planner: The requests in the auction pool are put together in sets to form more attractive sets called bundles.
3. Bidding by the freight forwarders: Each freight forwarder bids on the bundles generated in the previous step.
4. Winner determination by the central planner: The bundles get assigned to the freight forwarders in such a way that the overall profit for the coalition of freight forwarders is maximised.
5. Profit sharing for the freight forwarders: The profit gained by the request exchanges is distributed among the freight forwarders according to their contribution to the coalition.

By following this framework each freight forwarder is assigned a new set of requests to deliver to the ground handlers. In both the auction coopetition and full collaboration, the goal is to improve the overall profit of the coalition as opposed to the sum of the profits of the individual freight forwarders. In this project all five auction phases are modelled and solved. By comparing the auction coopetition to the individual planning and the full collaboration, the potential of the auction based coopetition is determined.

Transport efficiency is seen as one of the major opportunities for horizontal collaboration. In this thesis, transport efficiency is analysed on six different key performance indicators: profit, distance travelled, load factor, waiting time, amount of used trucks, and amount of truck arrivals. Additionally, the three collaboration types are evaluated on five possible disadvantages of collaboration: unfair profit allocation, loss of autonomy, ease of use, the need to share critical company information and the possible loss of market position.

A unique aspect of this project is that the dock capacity of the ground handlers is taken into account, i.e. there is a limited amount of docks available for the trucks to unload. Many cargo airports are struggling with truck congestion in the landside supply chain. By taking into account the dock capacity in the collaboration models the effect of introducing horizontal collaboration on the congestion can be analysed. Especially the waiting time and amount of truck arrivals are key indicators for the truck congestion. In the model developed in this thesis, the waiting time is directly related to the congestion, i.e. the waiting time is the total time trucks need to queue at the ground handlers. In practice, a reduction in the amount of trucks reduces the probability that a truck has to queue.

In the auction coopetition, there is a clear increase in profitability for the collaborating freight forwarders, because the auction model decreases the transportation costs for the entire coalition. This cost reduction is achieved by a decrease in the travelled distance, a decrease in the waiting time and a decrease in the amount of truck arrivals at the ground handlers. The clear decrease in congestion at the ground handlers, compared to the individual planning, is the result of two effects. Firstly, the central planner has an overview of all routing schedules and can adjust the routing of trucks such that queuing is avoided. Secondly, the request selection and bundling phases are designed such that requests that need to be delivered at the same ground handler have a high probability of being transported by the same truck.

In this thesis it is shown that the extra profit gained with the auction coopetition can be distributed in a fair way and it ensures that no freight forwarder loses profit compared to the individual planning. The auction coopetition is relatively easy to use for the freight forwarders and requires some input, like their cost structure. This information is not shared with the other collaborating freight forwarders. The auction coopetition only requires the freight forwarders to share limited non-critical company information with the central planner. In the auction coopetition some of the planning decisions are taken by a mathematical algorithm and not by the freight forwarders.

All in all, the auction coopetition has the benefits of a central planner, increases freight forwarders' profitability, reduces congestion at the ground handlers and preserves competition between freight forwarders, while keeping the collaboration disadvantages limited.

Contents

Acronyms

Acronym	Definition
A	Auction coopetition
ART	Allowed run time
CP	Central planner
DC	Dock capacity
F	Full collaboration
FF	Freight forwarder
GH	Ground handler
I	Individual planning
LSP	Logistic service provider
MILP	Mixed integer linear programming
MWDC-PDPTW	Multi-Warehouse Dock-Capacitated Pickup and Delivery Problem with Time Windows
SA	Simulated annealing
TW	Time window
VRP	Vehicle routing problem
WDP	Winner determination problem

1 Introduction

1.1. Current situation

The increase in demanding consumer lifestyles and the current societal search for sustainability call for an increase in efficiency of logistic service providers. Collaboration between logistic service providers has the potential to offer such efficiency, because collaboration can improve the performance of the overall transport system while saving transport costs. (Ferrell et al., 2019)

Vertical collaboration takes place between companies that operate on different levels of the supply chain, such as the manufacturer, the carrier and the retailer. This type of collaboration is already well established in many supply chain networks (Mason et al., 2007). In highly competitive industries, such as the air cargo transport industry, the development towards more integrated logistic service providers has increased the complexity and competitiveness for all levels of the supply chain.

Until now, freight forwarding companies in the air cargo supply chain were able to manage the complexity and competitiveness of the market with high margins, optimisation of their own resources and vertical collaboration. The emergence of integrative services, increased competitiveness with other transport systems and declining operations margins have motivated the air cargo transport industry to look into horizontal collaboration (Ankersmit et al., 2014). Horizontal collaboration occurs when companies that work at the same level of the supply chain decide to work together, rather than operate separately, with the goal to increase their efficiency. An overview of the air cargo supply chain is given in Figure 1.1

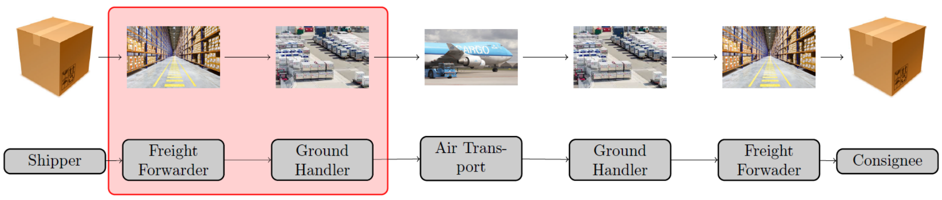

Figure 1.1: Air cargo supply chain, highlighted landside export (Bombelli and Tavasszy, 2020).

Freight forwarders (FFs) organise the transportation requests from shippers by finding a routing strategy for their trucks from the freight forwarding depot to the ground handlers (GHs) on the airport. FFs within the air cargo transport supply chain can, for instance, collaborate by sharing the capacity of transport vehicles, the booking and planning of transport requests from shippers and the handling of these requests.

Bombelli and Tavasszy (2020) developed a horizontal collaboration system for the air cargo supply chain. They presented a mathematical formulation, a landside air cargo supply chain problem with pick up and delivery time windows, to model horizontal collaboration between FFs for the transport of air cargo. The collaboration is modelled by assuming that a homogeneous fleet of trucks is shared by all freight forwarders. A central planner, with full information of the collaborating forwarders and all transport requests, computes the optimal routing strategy for the fleet. Wu (2019) developed a meta heuristic for this formulation to significantly decrease the computational time, which poses challenges for medium and large-sized instances. A new addition in that model is that they account for the maximum dock capacity at the ground handler's side. With an increase in shipments it occurs more frequently that the number of arriving trucks exceeds the dock capacity, leading to queuing, which is highly undesirable.

Recent studies show good results in improving reliability, use of resources, sustainability, congestion, costs, travel distance and other system performances (Wu, 2019), (Gansterer et al., 2019b), (Verdonck et al., 2013), (Berger and Bierwirth, 2010). However, the unwillingness of companies to share information is delaying the shift towards more horizontal collaboration (Gansterer et al., 2019a). According to Raweewan and Ferrell (2018) there is proof that supply chain collaborations mostly fail because of this resistance towards sharing information. A more complex form of horizontal collaboration that makes use of an auction based system may provide a solution. In this project the potential of an auction based horizontal collaboration system, is analysed, where the system preserves competition between freight forwarders and requires limited information to be shared. Such a type of collaboration is referred to as auction based coopetition.

In an auction based system transport requests can be exchanged without having to share critical company information (Gansterer et al., 2019b). All cooperating FFs submit transportation requests into a common auction pool. The requests are then bundled and offered for auction. The FFs bid on the offered bundles of transportation requests and the bundles are assigned to FFs based on their bids. In the final step the collected profits are distributed among the FFs. There are a multitude of types of auction based systems, variations can for example be found in the request selection and bundling, the bidding procedure and the profit sharing mechanism (Gansterer and Hartl, 2018).

1.2. Problem definition

To give a clear overview of the research problem first a short overview of the involved actors from Figure 1.1 is given:

1. Freight forwarders are located near but outside the airport. For a FF it is important that transport efficiency is increased, because (a) it could decrease their transportation cost, (b) it could lead to less missed flights, and (c) it could lead to less truck congestion.
2. Shippers own the commodities that are transported by the FFs. They expect a reliable service with a fair quality to cost ratio.
3. Airports demand an efficient ground handling network to stay attractive in the cargo market. With a less efficient supply chain, shippers and airlines may choose different airports.
4. Ground handlers connect the landside and air-side of the airport. After receiving cargo from FFs they load the unit load devices (ULDs) onto the aircraft. A less efficient supply chain could lead to a less reliable service and shippers may choose a different airport.
5. Airlines transport the cargo from origin to destination airport. A more efficient supply chain would lead to less relocations of delayed shipments.
6. The consignee is the receiver of the goods from the shipper. With a more efficient supply chain, they receive more of their goods on time.

A FF needs to move all of its shipments from the depot to the GHs located on the airport. The aircraft that transport the shipments are mostly on a tight schedule and can not be delayed by the late arrival of cargo. In addition, the GHs have limited amount of available space and they do not want to function as a storage depot. Therefore, to ensure on time arrival of the shipments, trucks generally perform many tours while not fully loaded. This leads to an inefficient way of using the available resources.

Another disadvantage of the limited available space at the GHs is the limited amount of available docks for unloading the trucks. When the number of arriving trucks exceeds the number of available docks, the trucks have to wait in a queue. This is highly undesirable for multiple reasons: 1. The waiting trucks and drivers cost money without being productive. 2. The queues themselves also have a limited capacity which could result in congestion further down the supply chain. 3. The truck queue(s) occupy valuable space on the airport.

This project continues on the research of Wu (2019), where it was shown that full collaboration improves the system performance on, among others, the two previously mentioned challenges: resource usage and truck queuing. However, assuming that freight forwarders would be willing to fully collaborate is not very realistic. They are competitors on the same level of the supply chain and are hesitant to share (critical) information with each other. Therefore, there is a need for an alternate collaboration strategy that increases transportation efficiency and preserves the competition between the FFs.

1.3. Objective

The main contribution of this project is to show how horizontal coopetition, in the form of an auction based system, affects the cargo transport from FF to GH in key areas. Transport efficiency is seen as one of the major opportunities for horizontal collaboration (Cruijssen et al., 2007). The goal is to evaluate the possible increase in transport efficiency, while keeping track of the underlying disadvantages of introducing an auction based coopetition system.

In the project an integrated and practical framework of a five phase auction model is introduced. The objective of the model is to obtain efficient truck routes from the FFs to the GHs. Another objective of this project is to address the following gaps in literature, identified in Chapter 2:

1. A fully integrated five phase auction model for the truck planning of the FFs. (Methodological contribution)
2. A comparison on transport efficiency between different types of collaboration: auction based coopetition, individual planning and full collaboration, while keeping track of the possible disadvantages. (Assessment of system potential)

For gap 1 a mathematical model is developed that is used as a tool to fill gap 2. The main focus will be on comparing three types of collaboration on transport efficiency. By keeping track of the disadvantages in the mathematical model a trade-off between the transport efficiency and the disadvantages of an auction based system is made.

1.4. Research Question

The main research question of this project is:

What are the key effects of introducing horizontal coopetition, in the form of an auction based system, on the transport efficiency of the landside air cargo supply chain?

With this main research question the goal is to evaluate the possible increase in transport efficiency when introducing an auction based coopetition system into the air cargo supply chain. By also keeping track of the possible disadvantages a trade-off between the increase in efficiency and these disadvantages can be made.

Sub-question 1: *How to quantify the transport efficiency of the landside air cargo supply chain?*

The focus of this project is comparing the transport efficiency, with key performance indicators (KPIs), of three different types of collaboration: auction based coopetition, no collaboration and full collaboration.

Sub-question 2a: *What are the disadvantages of horizontal collaboration in the landside air cargo supply chain?*

Sub-question 2b: *How to keep track of these disadvantages when modelling the auction based coopetition system?*

Sub-questions 2a and 2b focus on the possible disadvantages of horizontal collaboration, when it is implemented. Examples of possible disadvantages are: less autonomy for the FFs, an unfair profit sharing mechanism or the need to share critical company information.

Sub-question 3: *How does horizontal coopetition compare to the no collaboration and full collaboration models on transport efficiency and possible collaboration disadvantages?*

With the KPIs of sub-question 1 and the disadvantages of sub-question 2 a comparison is made between the different types of collaboration. This gives insight into the added value of the auction based coopetition system.

1.5. Thesis structure

In Chapter 2 a literature review is given for three main components of this project: congestion modelling, horizontal collaboration and information sharing between competitors. In Chapter 3, the methodology of this project is explained in detail. Sub-questions 1 and 2 about the KPIs and possible disadvantages are answered in Chapter 4. In Chapter 5 the auction coopetition model is presented with detailed descriptions of all five auction phases. In Chapter 6 the results of multiple data instances are presented. Finally, in Chapter 7 and Chapter 8 the discussion, conclusion and recommendations of the project are presented.

2

Literature Review

In this chapter, this project is placed in its scientific context. First, possible ways to include the congestion of the trucks into the model are discussed in Section 2.1. Second, related research on horizontal collaboration is discussed in Section 2.2. Subsequently, in Section 2.3 the resistance towards sharing information is explained. Finally, a synthesis of state-of-the-art studies related to the current research is given in Section 2.4.

2.1. Congestion

Many cargo airports are struggling with truck congestion in the landside supply chain (Verduijn et al., 2019). Congestion at the ground handlers on the airport can be categorised as a part of transport efficiency of the whole system. Therefore, part of this research is focused on analysing the effects of an auction based coopetition system on the truck congestion. Hence, a method to include truck congestion into the model is required.

Two main methods for modelling the congestion are identified. Firstly, in a mathematical model constraints can be added to avoid solutions that require more trucks arriving at a GH than the amount of available docks. This method is seen in cross-docking studies such as (Miao et al., 2009), (Choy et al., 2012) and (Shahram and Vahdani, 2019). The second method can be found in research about the Green Vehicle Routing Problem (Poonthalir and Nadarajan, 2019). In the Green Vehicle Routing Problem electric vehicles distribute goods to different locations. During their routes these electric vehicles have to recharge their batteries at charging stations. These stations have a limited number of service docks and vehicles have to queue, when all of the docks are occupied. This queuing is inefficient and most optimisation models do not take dock capacity constraints into account when computing the optimal routes. Bruglieri et al. (2019) address this issue by incorporating a reservation system for the charging docks into a Mixed Integer Linear Program (MILP). The main drawback of this method is that the arrival times of the vehicles are very unpredictable, which may cause queues or result in only partial refuelling of the vehicles. Poonthalir and Nadarajan (2019) propose a new Green Vehicle Routing Problem by adding a queuing formulation for the waiting time at service stations. Their research shows to what extend the waiting times at the service stations influence the route costs. They suggest that more research is needed to assess the impact of different queuing models.

2.2. Horizontal Collaboration

Studies until 2007 mainly focused on quantifying the potential cost savings using simulation and reporting a limited number of successful real life collaboration cases. Cruijssen et al. (2007) are the first to survey the potential benefits and impediments for joint route planning. They found that LSPs in Flanders believe that cooperation can increase the profitability and the quality of the service. The main impediments are finding a reliable partner to lead the collaboration and creating a fair benefit allocation mechanism.

Verdonck et al. (2013) give an overview of operational planning in horizontal collaboration for carriers divided into two categories: order sharing and vehicle capacity sharing. Order sharing is based on the exchange of transport requests, while capacity sharing is about two or more carriers sharing the capacity and the costs of a truck to lower capital investment costs and increase the utilisation rate of trucks. To our knowledge, there is no method that combines auctions and vehicle capacity sharing. Verdonck et al. (2013) also identify that few studies have focused on developing an extensive mathematical formulation for collaborative transportation that also takes into account practical considerations like: order characteristics, vehicle capacities and time windows.

Ankersmit et al. (2014) assessed the potential benefits of centralised collaborative planning between freight forwarders in the landside air cargo supply chain. Their research is based on a case study of Schiphol airport and includes multiple freight forwarders and only one ground handler. The inner airport distances are smaller compared to other transport systems. They used a simulation model to compare the performance of three different types of collaboration with a system without collaboration. They define two types of transport between the freight forwarders and the ground handler: 1) single transport, which only contains the shipments of one forwarding company, 2) combined transport, which can contain shipments belonging to two or more forwarders. This research is therefore classified as a 'capacity sharing' mechanism, as defined in (Verdonck et al., 2013). One of their key findings is that the transport costs can decrease up to 40%, while reducing the number of truck movements between freight forwarders and the cargo handler. One of the main issues of this approach is how to efficiently organise the remaining single company transport, once the combined transport is determined. Only when this aspect is also improved, the full potential of horizontal collaboration can be achieved.

Gansterer and Hartl (2018) give an overview of collaborative vehicle routing mechanisms divided into three categories:

A. Centralised collaborative planning, where a central authority has full information and therefore the problem becomes a standard optimisation problem.

B. Decentralised planning without auctions. This consists of three different phases: partner selection, request selection and request exchange. The exchange of requests is done by trading requests. Out of the three categories this is the least researched one.

C. Decentralised planning with auctions. This system consists of 5 phases which are defined by Berger and Bierwirth (2010):

   1. Request selection by the carriers. Every carrier selects requests based on predetermined characteristics, such as nearest distance to other requests or the requests with the lowest profit margins, to enter in the auction pool.
   2. Request bundling by the auctioneer or carriers. The requests in the auction pool can be put together in sets, for instance based on geographical locations, to form more attractive sets called bundles.
   3. Bidding by the carriers. Each carrier can bid on the bundles generated in the previous step. How this is executed depends on which bidding procedure is chosen.

4. Winner determination by the auctioneer. The bundles get assigned to the carriers in such a way that the overall profit for all carriers combined is maximised.
5. Profit sharing for the carriers. The profit gained by the request exchanges is split up among all participating carriers. This step also depends on which approach is chosen.

Generally it is assumed that trading requests is less complex than organising an auction with a bidding system. However, with auction based methods the profit sharing mechanism is sometimes already incorporated into the bidding mechanism, for instance in the Vickrey Auction (Verdonck et al., 2013). With centralised collaborative planing (A) and decentralised planning without auctions (B), a fair collaborative profit allocation system has to be identified as a separate step. Gansterer and Hartl (2018) highlighted that comparing the performance of a decentralised system with and without auctions is an interesting research direction.

According to Gansterer and Hartl (2018) each of the five phases of an auction based system is a complex optimisation problem in itself. They argue that most literature focuses either on the request exchange mechanism or on the profit sharing system. A complete and integrated framework including all five phases is missing. Two other proposed future work directions in (Gansterer and Hartl, 2018) are:

- A comparative study assessing the advantages of auction-based compared to non-auction-based systems.
- The assessment of the value of information in decentralised exchange mechanisms. How much does the solution quality increase with different types or levels of information?

Gansterer et al. (2018) investigate the trade off between four desirable characteristics in exchange mechanisms:

1. Efficiency: no further gains from request exchange are possible, i.e. the additional value created by reallocation is maximised.
2. Incentive compatibility: bidding the true value of a bundle is the optimal strategy for a FF.
3. Individual rationality: participating does not lead to a loss for a FF.
4. Budget balance: the auctioneer does not incur a loss or profit after reallocation.

Although they show that meeting all four properties is not possible, they do propose two incentive compatible methods that appear to be applicable in practice.

One of the most recent studies is that of Ferrell et al. (2019). They give an overview of existing research on horizontal collaboration, including but not limited to transportation. They divide the reviewed papers on freight consolidation into two categories: 1) Opportunities, impediments and facilitation, and 2) Mathematical and simulation models to quantify the benefits. The latter being the most researched one by far and showing some promising results. It is noteworthy that most researches in the second category mainly focused on improving the benefits and not on reducing the disadvantages of collaboration. Therefore, one of their recommendations is that additional studies are needed to asses advantages and disadvantages of horizontal collaboration.

Verdonck et al. (2013) and Berger and Bierwirth (2010) say that it is always beneficial for a cooperation to share more information. This may be true from a monetary perspective, but not from a competitive market perspective. Developing the best mathematical optimisation or heuristic method has been the main goal for most research. However, there is a high risk that FFs are not willing to join a mathematically perfect cooperation due to other disadvantages. In this project, a mathematically imperfect but good solution strategy is developed, where the attractiveness for the FFs to join the collaboration is taken into account.

2.3. Information

In most horizontal collaboration settings there is resistance towards the sharing of critical information. As an example, Ankersmit et al. (2014) do mention this resistance, yet they develop a collaboration mechanism which in practice requires the exchange of information. Their research was focused on assessing the potential of collaboration and not on how to manage this information exchange.

In centralised collaborative settings, such as in (Wu, 2019), it is assumed that a central planner has full information. Therefore, in these situations the most optimal collaboration solution can be found. In non-collaborative (individual) settings there is no exchange of information and every party optimises their own request fulfilment. There is not much research on quantifying the added value of exchanging more information.

Raweewan and Ferrell (2018) propose a framework for evaluating information exchange in potential collaboration mechanisms. They identify different situations in which sharing information is beneficial. In general they argue that companies should share information when the net value of collaborating exceeds the net value of not collaborating.

Gansterer et al. (2019b) propose an auction based collaboration system that uses only aggregated information of all requests of a carrier to determine which requests should be entered into the auction pool. To create request bundles, they only use a valuation of the individual requests in the auction pool. In this way, they ensure that no critical or sensitive information is inadvertently exchanged. With this method they increase the profit and reduce the number of generated bundles needed for a profit increase. A new profit sharing method is introduced that guarantees individual rationality and does not require sensitive or critical information from the collaborators.

2.4. Contribution

In Table 2.1 an overview of twelve studies and this master thesis can be found. The twelve studies represent the state-of-the-art in modelling horizontal collaboration related to this study. In the table for each study the type, full collaboration or auction based collaboration, is indicated. It is shown whether delivery time windows (TW), pick-up and delivery (PD) and dock capacity (DC) are taken into account. Additionally, the main focus of a study is shown as either a methodological contribution (MC) or an assessment of the potential of the horizontal collaboration (PA). Note that PA does not apply to studies that compare their methodological contribution with existing methodologies in literature, like Wu (2019) and Lyu et al. (2019). This is seen as an assessment of the potential of the solution methodology and not as an assessment of the potential of horizontal collaboration.

As can be seen in Table 2.1, most studies focus on a methodological contribution. For example, Lyu et al. (2019) define a new auction system where they show that a multi-round exchange mechanism provides 11.8% more profit compared to other mechanisms. The amount of existing studies that research the potential for the collaboration gain is limited. Both Ankersmit et al. (2014) and Gansterer et al. (2020) assess the potential of a full collaboration system. Furthermore, there are studies that evaluate strategies for individual auction phases. For instance Schopka and Kopfer (2017) and Gansterer and Hartl (2016) assess the potential of different request selection strategies. In Table 2.1 these studies are not denoted with PA. They do not assess the potential of the entire auction system, rather they compare options for a particular auction phase.

As can be seen in Table 2.1, the current research is unique as it takes into account time windows for delivery, pick-up and delivery, and dock capacity for an auction based collaboration system. The main contribution of the current research is twofold:

1. A fully integrated five phase auction model with delivery time windows, pick-up and delivery, and dock capacity. The auction phases are specially designed for the air cargo supply chain. (Methodological contribution)

2. A comparison on transport efficiency between different types of collaboration: auction based coopetition, no collaboration and full collaboration, while keeping track of the possible disadvantages. (Assessment of system potential)

Table 2.1: Overview of basic characteristics of existing literature.

Reference	Type [a]	TW[b]	PD[c]	DC[d]	Focus[e]	Main contribution
Berger and Bierwirth (2010)	A		✓		MC	Framework for auction based collaboration.
Ankersmit et al. (2014)	F		✓		PA	Real-world air cargo case study.
Gansterer and Hartl (2016)	A	✓	✓		MC	Analysis of request selection strategies.
Gansterer et al. (2019b)	A		✓		MC	Improvement of auction phases and new profit sharing mechanism.
Wu (2019)	F	✓	✓	✓	MC	Air cargo application with dock capacity
Chen (2016)	A	✓	✓		MC	Improvement of auction phases with clock-proxy strategy.
Li et al. (2016)	A	✓	✓		MC	Addition of reserved requests.
Schopka and Kopfer (2017)	A	✓			MC	Analysis of request selection strategies.
Lyu et al. (2019)	A		✓		MC	Auction with multiple rounds.
Defryn et al. (2019)	F		✓		MC	Integrating partner objectives in horizontal collaboration.
Gansterer et al. (2020)	F	✓	✓		MC & PA	Cost saving potential of centralised collaborative frameworks.
Shao et al. (2020)	A	✓	✓		MC	Truthful bidding encouraged by bidding time windows.
van Alebeek (2020), current thesis	A	✓	✓	✓	MC & PA	Auction coopetition in air cargo industry.

[a] F: Full collaboration, A: Auction based collaboration
[b] TW: time windows of delivery are taken into account.
[c] PD: pick-up and delivery are considered.
[d] DC: dock capacity is taken into account.
[e] MC: methodological contribution, PA: assessment of the potential of the collaboration system.

3 Methodology

In this chapter, the methods applied in this project are described. In Figure 3.1 the methodology framework can be found. The focus of this project is on comparing the transport efficiency, of three types of collaboration, on key performance indicators (KPIs). Meanwhile, for all three types of collaboration, the possible disadvantages of collaboration are tracked. In Figure 3.1 the two green boxes represent the first and second sub-question from Section 1.4, about the KPIs and the disadvantages. The three types of collaboration that are compared are: auction based coopetition, individual planning and full collaboration. These models are represented by the blue boxes in Figure 3.1. To answer the main research question all three models are compared on the defined KPIs and disadvantages, shown in the orange box in Figure 3.1.

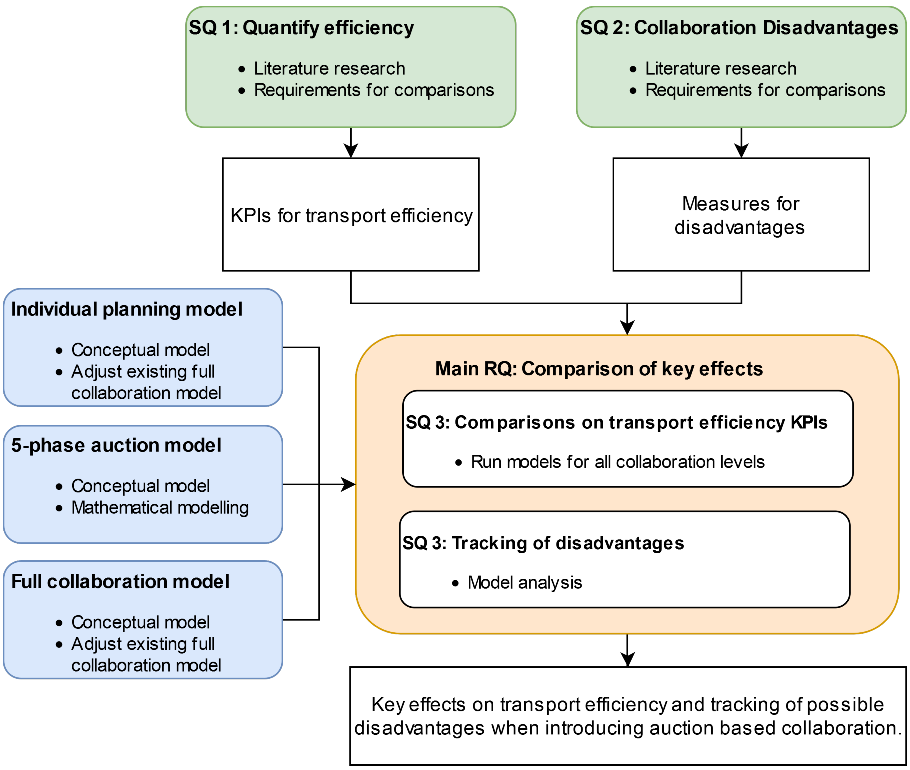

Figure 3.1: Diagram of Methodology.

3.1. Approach and scope

To analyse the key effects of the auction based coopetition a comparison between three types of collaboration is made: Individual planning, Auction based coopetition and Full collaboration. The comparison is based on KPIs and other performance measures found in literature, these are described in detail in Chapter 4.

The three collaboration types are based on the Multi-Warehouse Dock-Capacitated Pickup and Delivery Problem with Time Windows (MWDC-PDPTW) created by Bombelli and Tavasszy (2020). They used an exact solution method and (Wu, 2019) used a meta heuristic to solve the MWDC-PDPTW. In this project the meta heuristic is used as a basis for the solution method of the indvidual planning and the full collaboration. The meta heuristic is based on a simulated annealing framework, where an adaptive large neighbourhood search is used to explore the neighborhood of the current solution. A more detailed explanation of the meta heuristic is given in Section 3.4.

A concise explanation of the three collaboration types is given below, the corresponding graphical overviews can be found in Figures 3.2, 3.3 and 3.4. The small squares represent the initial requests of a FF, where 1-4 belong to FF1, a-d to FF2 and i-iv to FF3. In the individual planning each FF has to transport all of its requests to the GHs with his own trucks. A graphical representation of the individual planning is shown in Figure 3.2.

In the full collaboration the central planner has full information on the shipments of every FF in the coalition. Therefore, the problem can be seen as if the central planner is one large FF that needs to transport all the requests of the coalition. This is modelled by using a neutral fleet of trucks belonging to all (or no) FFs. The central planner assigns all requests to trucks in such a way that routing costs are minimised. A graphical representation of the full collaboration is shown in Figure 3.3.

The main difference between the full collaboration and the auction coopetition is the method for assigning requests to the FFs. The assignment of the requests to the collaborating FFs is done by means of five integrated auction phases, proposed by Berger and Bierwirth (2010). In the auction coopetition the central planner also acts as auctioneer. Additionally, the FFs are seen as individual companies that are all responsible for the transportation of their assigned requests. A graphical representation of the auction coopetition is shown in Figure 3.4. The five phases are as follows:

1. Request selection by the FFs: Every FF selects requests based on predetermined characteristics to enter in the auction pool.
2. Request bundling by the central planner: The requests in the auction pool are put together in sets to form more attractive sets called bundles.
3. Bidding by the FFs: Each FF bids on the bundles generated in the previous step. A bid is based on the marginal profit for a FF of handling that specific bundle.
4. Winner determination by the central planner: The bundles get assigned to the FFs in such a way that the overall profit for all FFs combined is maximised.
5. Profit sharing for the FFs: The profit gained by the request exchanges is divided among all participating FFs.

The auction coopetition is the main focus of this project. The five auction phases from Berger and Bierwirth (2010) form the basis for the solution method of the auction coopetition. In this project all five auction phases are modelled and solved. By comparing the auction coopetition to the individual planning and the full collaboration, the potential of the auction based coopetition is determined. Initially, the five phases of the auction will be kept simple and are based on a set of practical and operationally reasonable rules. Then, once the whole framework is operational, additional complexity is added to the phases with the highest priority. During the project a priority list is maintained with possible additions to the model.

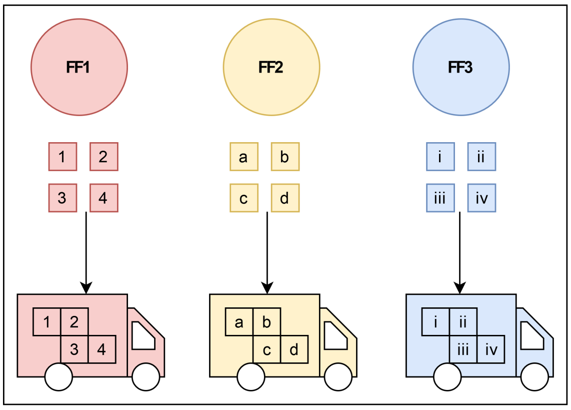

Figure 3.2: Diagram of individual planning.

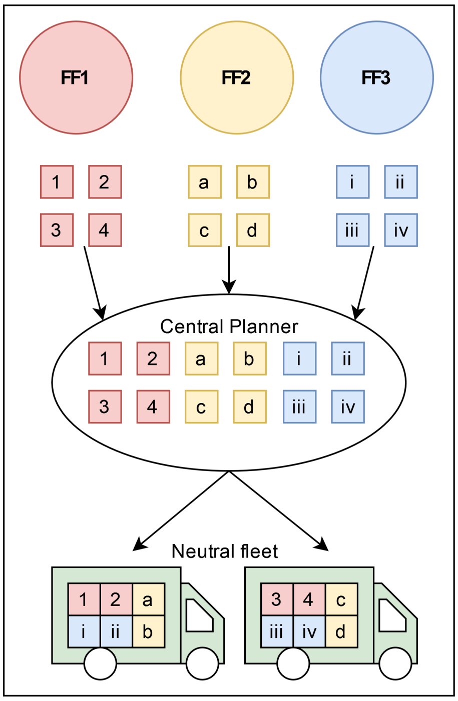

Figure 3.3: Diagram of full collaboration.

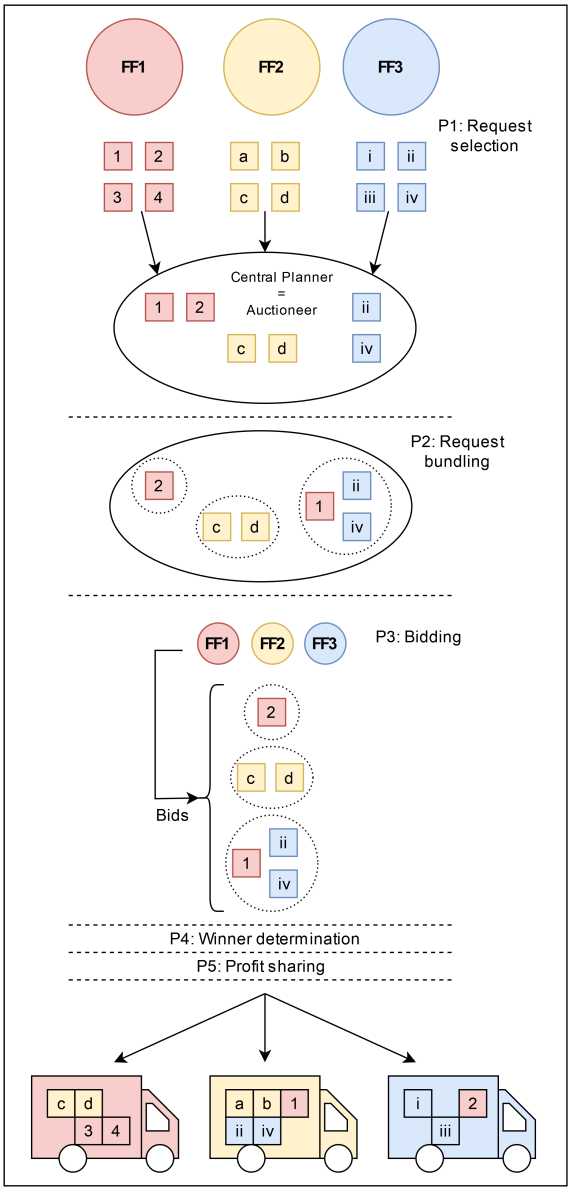

Figure 3.4: Diagram of auction based coopetition.

In this project the following question is left out of scope: Why is horizontal collaboration not yet implemented in a real world air cargo supply chain? This question focuses more on the impediments for the introduction of such a system. For example, finding commensurable collaboration partners proves very difficult or freight forwarders are currently unaware of the collaboration possibilities. Although investigating these impediments is outside the scope of this project, some of the disadvantages found by answering research sub-question 2 could also be impediments for the implementation of a collaborative system.

3.2. Problem statement

In both the auction coopetition and full collaboration a consortium of FFs agrees to collaborate to perform export deliveries to GHs. Each FF has a set of requests that have to be transported from the location of the FF to certain GHs within a specified planning horizon. At the same time, the GHs involved in the initiative agree to reserve a subset of their export docks for trucks belonging to the consortium. The goal of the coalition is to find a more attractive planning solution for all involved parties compared to a non-collaborative (individual planning) scenario.

A central planner supervises the collaboration and defines:

(1) a new request allocation, i.e. which FF will handle which request.
(2) a routing strategy for each truck, i.e. a sequence of FFs and GHs to visit.
(3) a loading strategy, i.e. a sequence of requests to be picked up and then delivered.
(4) a dock assignment strategy, i.e. a truck-dock pair for every warehouse visited.

For these steps, the goal is to improve the overall profit of the consortium as opposed to the summation of the profits of the individual FFs. Given the size and complexity of the problem, the goal is not necessarily to solve each problem to optimality. Rather, the goal is to demonstrate that by adhering to the rules of the consortium, every FF is more profitable than if it continued to operate as a single entity. In the individual planning each FF defines their routing strategy, loading strategy and dock assignment strategy, not taking into account the requests of the other FFs.

In each of the three collaboration types, each request is mapped by two nodes, a pickup node on the FF side and a delivery node on the GH side. All pickup and delivery nodes are characterised by a time window, which means that each request must be handled within a finite time frame. It is possible to add a maximum ride time for each request, this could be crucial for modelling the route planning of perishable goods. In this project only non-perishables are considered. It is assumed that all requests are consolidated at the FFs or upstream in the supply chain. Therefore, trucks are only moving unit load devices (ULDs). The dock capacity is only considered on the delivery side for the GHs. This assumption is justified, because GHs are generally the bottleneck in the landside air cargo supply chain.

In addition, two restrictions that are specific to the air cargo supply chain are added. (1) To ensure an efficient loading strategy for the trucks, all pickups precede all deliveries in a truck tour. (2) To model rear-loading of the trucks and to avoid unnecessary unloading at intermediate GHs, deliveries are carried out in reverse order with respect to pickups in a Last-In-First-Out (LIFO) approach. This requirement is especially crucial because in this project the ULDs occupy most of the lateral space in the trailers.

3.3. Mathematical problem formulation

The problem is based on a directed graph $G = (\mathcal{N}, \mathcal{E})$, where $\mathcal{E}$ is the set of edges and $\mathcal{N}$ is the union of four node sets: $\mathcal{N} = \mathcal{O}_d \cup \mathcal{N}_\mathcal{P} \cup \mathcal{N}_\mathcal{D} \cup \mathcal{D}_d$. $\mathcal{O}_d$ and $\mathcal{D}_d$ represent the origin and destination depot for the trucks, which generally are the same physical depot, but are distinct depots from a graph perspective. An unused truck has a trip with zero cost from $\mathcal{O}_d$ to $\mathcal{D}_d$. The cardinality of the set of pickup nodes ($\mathcal{N}_\mathcal{P}$) and the set of delivery nodes ($\mathcal{N}_\mathcal{D}$) is σ, where σ is the number of shipments to be delivered. The nodes are enumerated as follows: $\mathcal{O}_d$ is node 0, pickup nodes $\mathcal{N}_\mathcal{P}$ range from 1 to σ, delivery nodes $\mathcal{N}_\mathcal{D}$ range from $\sigma + 1$ to 2σ and $\mathcal{D}_d$ is node $2\sigma + 1$. Each request (r_i) consists of a pickup and delivery node pair: $(i, \sigma + i)$.

The sets of nodes $\mathcal{N}_\mathcal{P}$ and $\mathcal{N}_\mathcal{D}$ are grouped into blocks depending on their origin-destination (OD) pair. The set of $N_\mathcal{F}$ FFs is denoted with $\mathcal{F} = \mathcal{F}_1, \cdots, \mathcal{F}_{N_\mathcal{F}}$ and the set of $N_\mathcal{G}$ GHs is denoted with $\mathcal{G} = \mathcal{G}_1, \cdots, \mathcal{G}_{N_\mathcal{G}}$. Each FF is characterised by $N_\mathcal{G}$ blocks $\mathcal{B}^\mathcal{F}_{fg}$, containing the pickup nodes of requests stored at FF f that must be delivered at GH g. Similarly, each GH is characterised by $N_\mathcal{F}$ blocks $\mathcal{B}^\mathcal{G}_{fg}$, containing the delivery nodes of requests stored at FF f that must be delivered at GH g. $\mathcal{B}^\mathcal{F}_{fg}$ and $\mathcal{B}^\mathcal{G}_{fg}$ contain the same amount of nodes, since they either store the pickup or the delivery node of a request going from FF f to GH g.

Each node $i \in \mathcal{N}_\mathcal{P}$ is characterised by a time window $[e_i, l_i]$, where e_i and l_i represent the earliest and the latest start of the processing time of node i, respectively. In order to satisfy the time window constraint, the inequality $e_i \leq \tau_i \leq l_i$ must hold, where τ_i is defined as the time at which the processing of node i starts. The same constraint holds for all $\sigma + i \in \mathcal{N}_\mathcal{D}$. Additionally, each node is characterised by a processing time p_i, that defines the amount of time it takes to load or unload a request. Furthermore, $t_{i,\sigma+i}$ denotes the amount of time it takes a truck to go from node i to node $\sigma + i$, including the time it takes the truck to reverse into a docking station. To ensure feasibility of a data instance, the inequality $l_{\sigma+i} \geq e_i + p_i + t_{i,\sigma+i}$ must hold for request i.

For each GH g, $N^g_\mathcal{D}$ denotes the number of available docks. For computational reasons, the number of available docks at each GH is set to 1 in this project. If the number of available docks is increased, it would take a much larger instance to have a tight dock capacity constraint. Each FF f owns a fleet $\mathcal{T}^f$ composed of $N^f_\mathcal{T}$ trucks. Each truck $\mathcal{T}^f_k \in \mathcal{T}^f$ is characterised by the same maximum weight capacity Q and the same maximum space capacity $\mathcal{L}$. For this project it is assumed that each truck is allowed to start and finish its route at any time on the problem horizon. Additionally, the fleets of the FFs are considered to be identical and homogeneous.

Part of the output of the models for each collaboration type is a list of routes for a subset of $\mathcal{T}^f$ for each FF f. Each route is a sequence of nodes, where the first node is $\mathcal{O}_d$ and the last node is $\mathcal{D}_d$. Between the origin and destination depot nodes, a subset of pickup nodes from $\mathcal{N}_\mathcal{P}$ and the associated delivery nodes from $\mathcal{N}_\mathcal{D}$ (in reverse order) complete each route.

All commonly used notation is summarised in Tables 3.1 and 3.2. Additional notation more specific to certain parts of the auction coopetition model are explained in the corresponding sections in Chapter 5.

Table 3.1: Sets for the auction based coopetition model

Set	Cardinality	Description
$\mathcal{R}$	σ	Requests
$\mathcal{N}_P$	σ	Pickup nodes
$\mathcal{N}_D$	σ	Delivery nodes
$\mathcal{N}$	$2\sigma + 2$	Nodes
$\mathcal{E}$	$\sigma + 2\sigma^2 + 1$	Edges
$\mathcal{T}$	N_t	Trucks
$\mathcal{F}$	$N_\mathcal{F}$	Freight forwarders
$\mathcal{G}$	$N_\mathcal{G}$	Ground handlers
$\mathcal{B}^\mathcal{F}_{fg}$		Pickup nodes with pickup at FF f and delivery at GH g
$\mathcal{B}^\mathcal{G}_{fg}$		Delivery nodes with pickup at FF f and delivery at GH g

Table 3.2: Parameters for the auction based coopetition model

Parameter	Description
$[e_i, l_i]$	Time window to visit node i, early and late time
d_{ij}	Distance between node i and j
t_{ij}	Time it takes to go from node i to node j
p_i	Processing time of node i
q_i	Weight of request i
z_i	Width of request i
Q	Maximum weight transportable by truck
L	Maximum lateral occupancy transportable by truck
c_τ	Transportation cost per time unit
$N_{\mathcal{D}}^g = 1$	Number of docks available at GH g
rev_i	Revenue of node i
P_i	Pickup location of request i
D_i	Delivery location of request i

3.4. MWDC-PDPTW meta heuristic

To solve the MWDC-PDPTW, Wu (2019) created a meta heuristic with a simulated annealing (SA) structure. SA is often used to approximate the global optimum of a large solution space of an optimisation problem. In each iteration of the SA a neighbour solution S^* of the current solution S_c is considered. If the neighbour solution S^* is better than the current solution, this becomes the new current solution, $S_c = S^*$. If the new solution is not better than the current solution, the new solution S^* is accepted as the new current solution with a predetermined probability. Exploring these sub-optimal solution regions might lead to a better final solution

Part of the input of the meta heuristic is the set of requests that need to be shipped. By adjusting the set of shipments the meta heuristic of Wu (2019) can be used to calculate the full collaboration costs and the individual planning costs. To calculate the full collaboration costs the set of requests is equal to all requests of all FFs. To calculate the individual planning costs for one FF the set of requests is set to only the requests from that specific FF.

The cost (J) of a solution (S) is determined by the total amount of time it takes to deliver all requests to the GHs (TTT_S) and a predetermined transportation cost per time unit (c_τ): $J(S) = c_\tau * TTT_S$. The objective of the meta heuristic is to find a routing solution with the least amount of costs and thus the least amount of total transportation time. Additional costs are added to the objective function if the solution is infeasible. There are two types of infeasibilities for a solution:

1 Infeasibilities that can be solved by a time-shifting manipulation of the solution S, e.g. a violation of a dock capacity constraint. This is called a weakly infeasible solution.
2 Infeasibilities that can not be solved by a time-shifting manipulation of the solution S, e.g. a violation of the maximum capacity of a truck. This is called a strongly infeasible solution.

The strongly infeasible solutions are not considered. The cost function of a weakly infeasible solution is equal to the original cost function plus a penalty for the infeasibility.

In this project the total amount of allowed run time is predetermined for every SA performed. Normally the probability of accepting a worse neighbour solution as the new current solution depends on a temperature T that decreases with every iteration. In this project the temperature T is equal to the amount of time that is left of the total allowed run time for the SA. For example: the SA is allowed to run for 60 seconds, $T = 60$. The first iteration takes 5 seconds, $T = 55$ seconds. T decreases until the total allowed run time is used and the SA terminates. The probability of accepting neighbour solution S^*, if $J(S^*) > J(S_c)$, is determined by the following probability function: $P(S^*) = exp\,[(\,J(S_c) - J(S^*))/(T)]$.

In each iteration of the SA framework a new neighbour solution is found with a Large Neighbourhood Search (LNS). The LNS generates a new solution $S*$ from the current solution S_c by removing requests from a route and then inserting requests into a route. The removal operators are:

1. Shaw removal (Shaw, 1997)
2. Random removal
3. Worst removal
4. Shortest route removal
5. FF-GH removal

The insertion operators are:

1. Basic greedy insertion
2. Tabu greedy insertion
3. 2-Regret insertion
4. Route addition

The first three removal and first two insertion operators are taken from (Ropke and Pisinger, 2004), adjusted by (Bombelli and Tavasszy, 2020). The fourth removal operator is taken from (Li et al., 2015), adjusted by (Bombelli and Tavasszy, 2020). The third insertion operator is described by Ropke and Pisinger (2004). The fifth removal operator and the fourth insertion operators are from (Bombelli and Tavasszy, 2020).

After a removal and insertion pair has produced a new neighbour solution S^*, a routine is carried out to identify and reduce dock capacity violations without increasing other violations. In fact, while in the computation of J the overall dock capacity violation of the new solution is considered, no preemptive action is explicitly taken to limit such violation. The routine consists of two stages: time slack strategy and departure time adjustment strategy. For example, if two trucks arrive at the same dock at the same time, the time slack strategy tries to resolve the dock capacity violation by making one of the trucks wait until the other truck completes the unloading routine. The truck with the most time slack in their route is the truck that has to wait. The time slack of a route is explained in more detail in (Bombelli and Tavasszy, 2020).

If it is possible to resolve the dock capacity violation with the time slack strategy without causing other violations, the departure time adjustment strategy is applied. If this is not possible the solution is discarded. With the departure time adjustment strategy it is possible to prevent waiting times (caused by early arrival) by adjusting the departure times of the trucks. If, for example, a delayed truck has to wait for 5 minutes for another truck to unload, it would have been better if that delayed truck left the origin depot (O_d) 5 minutes later. In that case the truck would not have to wait the extra 5 minutes. Whether delaying the departure of a truck is possible is also based on the time slack of a route. In the individual planning, a FF is not aware of the planning of other FFs. Therefore, the time slack strategy and departure time adjustment strategy can not be used for the individual planning. However, in the individual planning trucks do have to queue, this is modelled using only the time slack strategy.

3.5. Data

In this section the most important aspects of the used data are discussed. A more detailed overview of the input data can be found in Appendix C. The data used in this project is artificial and largely based on data from previous research. Each data instance is generated based on the number of specified FFs and GHs. The number of requests between each FF-GH pair is randomly set between 2-7.

The distances between the FFs and GHs used in this project are based on the real world locations of the largest FFs and GHs on Schiphol airport. The distance matrix can be found in Appendix C. The average speed of each truck is set to 35 km/h, because distances are relatively short and the roads used are local low speed roads. The docking time of a truck (the amount of time it takes to reverse into a dock) is set to 2 minutes. In this project a request is either a container or a pallet with equal probability. The differences between a pallet and a container are their size, weight and processing time, more details can be found in Appendix C. The requests are assumed to already be consolidated at the FF or elsewhere upstream in the supply chain. The transportation cost per minute (c_τ) is based on a research by the American Transportation Research Institute (2018). They found a time cost of 66.65 dollars per hour, which translates to approximately 1.02 euros per minute.

The planning time horizon in this project is set to 480 minutes. Each request gets a delivery time window of three hours. If the delivery can take place at the end of the planning horizon the time window becomes: $[300, 480]$. Half of the requests gets a delivery time window earlier than the end of the day. Assuming that multiple requests at a GH have to be loaded into the same aircraft, it makes sense that those requests have the same time window for delivery. Therefore, the delivery time window depends on which GH the request has to be delivered to. Each GH has a set of possible delivery time windows. For example: GH 1 has to load 12 requests on different aircraft. Half of these requests are allowed to arrive at the end of the planning horizon, because the aircraft leave after $T = 480$. The other half of these 12(=6) requests get an earlier time window than $[300, 480]$. Assume that there are 3 different aircraft leaving during the day, meaning three different possible time windows for the requests, for instance: $[50, 230]$, $[130, 310]$, $[210, 390]$. The 6 requests, that do not have a time window at the end of the day, get assigned a time window chosen randomly out of these three time windows.

The following characteristics of the requests are specified in the data instances:

1. Node identification number.
2. Node type (pick up or delivery).
3. FF identification number for request pick up.
4. GH identification number for request delivery.
5. FF location, based on real world locations as specified above.
6. GH location, based on real world locations as specified above.
7. ULD type (container or pallet).
8. ULD weight, based on (Ankersmit et al., 2014).
9. ULD width, based on (Ankersmit et al., 2014).
10. ULD processing time.
11. Node time window
12. Node revenue, which is only used to show the resulting profits of the different collaboration types after computing the routes of the collaboration types. The revenue is never used in the calculation of the routes.

The Python code used to create data instances can be found in Appendix C. As can be seen in this chapter, the artificial data used in this project is largely based on previous research or logical reasoning. The data instances are a smaller yet accurate representation of a real world air cargo supply chain.

4

Performance measures and indicators

An overview of the KPIs used to quantify the transport efficiency of the collaboration types is given in Section 4.1. Additionally, the possible disadvantages of horizontal collaboration, that are tracked in this project, are explained in Section 4.2.

4.1. Quantifying transport efficiency

In the landside air cargo supply chain, efficiency can be measured in different ways. To capture the transport efficiency of the overall transportation system, several KPIs are required. Trying to reflect the transport efficiency in one single KPI will result in a non-transparent equation. Comparing the KPIs of one collaboration type to another shows the difference in performance on many different aspects of efficiency. It is also interesting to not only compare the overall system performance, but also the performance per FF. In this project, the following KPIs are used:

1. Profit
2. Distance travelled
3. Load factor
4. Waiting time for a dock to become available
5. Amount of trucks
6. Amount of truck arrivals at GHs

4.1.1. Profit

The profit made by a FF is equal to the revenue minus the costs for transporting the requests to the GHs. The revenue and costs made by a FF in this project are based on artificial input parameters. Therefore, the absolute value of the profit is not very informative. On the other hand, comparing the profit (per FF) of the different collaboration types does provide valuable information. The total profit of a collaboration type is equal to the sum of the profits of the FFs. It is important to note that, in this project, each FF keeps its initial revenue. Because FFs have contracts with shippers that hire them, it is most logical that those shippers pay the initial FF, even if in the final planning their request is transported by another FF. The reassignment of the profit will be discussed later, but should not be a responsibility of the shipper. Consequently, the difference in percentage of the total profit between the types of collaboration gives insight into the cost efficiency of the overall transportation planning. In this project, the costs for a FF only depend on the amount of time it takes to transport the requests to the GHs.

This KPI is especially important to see the overall time efficiency of the entire transportation planning and it is of great importance to the FFs. If more profit can be obtained by collaborating with other FFs, they may consider working together. Next to the total profit of a collaboration type, the profit per FF provides insight into the cost efficiency of each individual FF. The profit per FF is, for instance, required to show how fair the profit allocation of a collaboration type is, as explained in Section 4.2.1.

4.1.2. Distance travelled

The distance travelled of a collaboration type is defined as the sum of the distances driven by the trucks, including the distance from the origin depot ($\mathcal{O}_d$) and the distance to the destination depot ($\mathcal{D}_d$). Because the costs only depend on the transportation time, the distance is chosen as a separate KPI. Obviously, it takes time to travel a certain distance, so the distance is implicitly incorporated in the costs. In general it can be said that a planning with shorter routes, i.e. fewer kilometres, is more efficient. Another reason to track the travelled distance is that it is an indicator of the environmental impact. Simply put, less distance travelled means fewer carbon emissions. So, by comparing the travelled distance of the different collaboration types, some insight is gained in the route efficiency and environmental impact of the overall transportation planning.

4.1.3. Load factor

In this project there are two maximum capacities of the trucks, a weight capacity and a width capacity. Accordingly, there are two load factors, the weight load factor and the width load factor. Both load factors of a collaboration type are defined as the truck average of the used capacity divided by the total capacity. A higher load factor means that the trucks are fuller, which indicates a more efficient use of resources like trucks and drivers. Additionally, it is an indicator of the environmental impact. A higher load factor means less trucks are required for the transportation of the requests.

4.1.4. Waiting time

The waiting time is defined as the time a truck has to wait at a GH because there is no dock available at that time. It is important to note that the time a truck has to wait due to early arrival at a node (arriving before the early time of a time window) is not included in this KPI. It is possible that a queue of trucks forms if more trucks arrive than there are docks available at a GH. As soon as a dock becomes available the first truck in the queue is assigned to this dock. The total waiting time of all trucks in a collaboration type gives insight into the amount of congestion at the GHs. With higher waiting times there is more congestion at the GHs, so the planning is less efficient. By comparing the waiting times of the different collaboration types, the effect on the amount of congestion at the GHs can be monitored.

4.1.5. Amount of trucks

This KPI is simply the amount of trucks that are used in the planning of a collaboration type. The amount of trucks is tracked because it is an indicator of the total truck operating costs required for that collaboration type, such as truck maintenance and depreciation. A reduction in the amount of required trucks reduces these operating costs for the coalition or for an individual FF.

4.1.6. Truck arrivals

Besides the waiting time at the GHs, the amount of truck arrivals at a GH can also provide insight in the truck congestion at the GHs. A truck arrival is defined as a truck that docks at a GH. This means that one truck can have multiple truck arrivals if it visits multiple GHs. If at one GH two different trucks have to deliver requests, the amount of truck arrivals at that GH is equal to two. The truck arrivals KPI is the sum of all truck arrivals at all GHs for a collaboration type. Note that, the side of the FFs is not taken into account in this KPI. Additionally, this KPI is not related to the amount of trucks used or the load factor of the trucks. For instance, one truck can have more truck arrivals than multiple trucks combined. Fewer truck arrivals indicate a more efficient planning and a lower likelihood of congestion at the GHs.

4.2. Collaboration disadvantages

Although collaboration has been identified as a key factor in reducing transportation costs and increasing efficiency in most supply chains, its implementation is still not fully developed. This is mainly due to several factors that are perceived by stakeholders as disadvantages. Examples of possible disadvantages are: less autonomy for the freight forwarders, an unfair profit sharing mechanism or the need to share critical company information. In the following sections the most important disadvantages of horizontal collaboration, found in literature in Chapter 2, are explained in more detail. For each of the disadvantages, the corresponding section starts with a definition. Next, the way the disadvantage is tracked in the collaboration types is explained. Since the individual planning has no form of collaboration between the FFs, this is set as the benchmark for the other two types of collaboration. In Section 6.2 the performance of the full collaboration and auction coopetition on the disadvantages is compared to the benchmark. Finally, in Section 6.3 the transport efficiency and collaboration disadvantages are summarised in a trade-off.

4.2.1. Profit allocation

When FFs work together and obtain an increased joint profit, this profit needs to be divided over all participating FFs. The profit reallocation is done in the fifth auction phase. To make it attractive for different FFs to participate in the auction the profit should be divided in a fair way. In this project, fair profit allocation is defined as:

1. All FFs make at least the same amount of profit after the profit reallocation compared to the individual situation (individual rationality).
2. FFs get higher profit shares if they contribute more to the total collaboration gain (proportional to contribution).

The first point can easily be checked by comparing the profit of a FF when participating in the auction to the profit of their individual planning. Another option is to ensure that no FF has less profit after the auction by compensating for their individual loss. To track this, the individual profit and the profit after collaboration for all FFs has to be calculated. For the second point, the contribution to the total coalition gain of each FF needs to be identified. A FF can contribute in two ways: by buying requests or by selling requests. The contribution of a FF is tracked by the amount or value of the requests that each FF sells and/or buys.

4.2.2. Autonomy

When different FFs collaborate they agree on a set of rules for their collaboration. These rules can restrict the FFs in making individual decisions. Generally, autonomy is a fairly wide encompassing term, for which many different definitions exist. Considering the goals of this project, the focus of the autonomy disadvantage is on the freedom of a FF in its decisions in the various collaboration types. These decisions are for example, which request goes into which truck, which requests to keep for themselves and truck routing. In this project the autonomy of a FF depends on how restricted they are in making these decisions. If there are moments where a FF is obliged to comply with the coalition rules, the autonomy of a FF decreases.
The autonomy of the FFs in an auction based system is not captured in a single KPI. Instead, an overview of the autonomy is given for each of the collaboration types. This overview contains:

1. How many decisions may the FFs make themselves.
2. How the decisions are made: predetermined mathematical formulation or input from the FF.
3. From which perspective the decisions are made. Are the decisions in the best interest of the individual FF or are they focused on finding the best solution for the entire coalition?

4.2.3. Ease of use

In the individual planning each FF has a set of requests that need to be transported to the ground handlers. In the auction coopetition and the full collaboration, the most tangible change is the set of requests each FF has to deliver. Thus, for the FFs the principle of transporting requests to the GHs does not change. The major change for the FFs is a new request exchange mechanism. The ease of use for a FF depends on the amount of times a new action is required. A new action is for example choosing the amount of requests a FF wants to keep (k_i) or generating a bid in the auction process.
There is a trade-off between the autonomy of a FF and the ease of use for a FF. If a FF needs to make extra decisions they keep more of their autonomy but the system may become less easy to use. To track the ease of use, the amount of extra actions needed from the FFs to ensure a well functioning planning system is identified.

4.2.4. Information sharing

For the collaboration systems different types and amounts of information are required, ranging from request weight to the marginal profit of an auction bundle. Sharing certain types of information, e.g. request revenue, can be undesirable for FFs, because competitors could use this information in their advantage. Also, the party with whom the information is shared is relevant, sharing with a neutral central planner is different than sharing with a competing and collaborating FF. The overall shared information is not captured in a single KPI. Instead, an overview of the shared information is given for each of the collaboration types. This overview contains:

1. The amount of information required for each auction phase.
2. The type of information required for each auction phase.
3. With whom the information is shared.

4.2.5. Market position

The market position of a FF is determined by its share of the transportation market compared to the shares of its competitors. In this project the absolute market share of a FF is not tracked, because the data is artificially generated. Instead, the focus is on information sharing and especially how this can affect the market position of the FFs.
A possible downside of collaboration is that competitors (FFs) could obtain information about each others pricing. With this information they could try to undercut their competitors, causing them to lose market share. To see if this could happen in the collaboration types, two aspects should be monitored:

1. The amount and type of critical information that is shared by the FFs. Note that this is covered in Section 4.2.4.
2. Implicit information that can be retrieved from the redistribution of the requests. As an example: FF2 notices that he usually gets assigned the requests of FF1. From this, FF2 can deduce that it is possible that FF2 can transport the requests of FF1 cheaper. With this information, FF2 could decide to undercut FF1, causing FF1 to lose market position.

5

5-Phase auction model

The overall auction model consists of five phases. Each of the five phases requires input from the previous phase or additional data such as locations of the FFs and GHs. In Figure 5.1 a graphical overview of the five phases can be found.

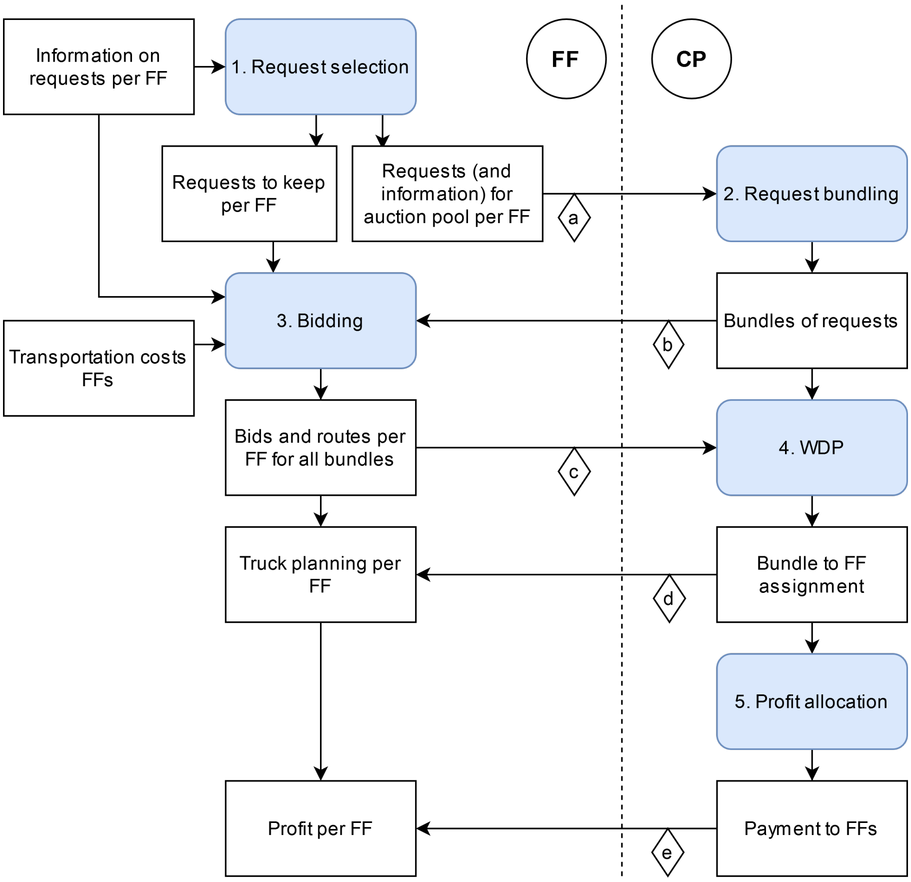

Figure 5.1: Overview of the auction model. Left: actions by the FFs. Right: actions by the central planner (CP). Horizontal arrows represent information exchanges between the FFs and CP and vice versa. Explanation of the ◊ symbols can be found in Section 6.2.4.

5.1. Request selection

In this phase all FFs individually decide which requests they want to keep and which requests they want to submit to the auction pool. This decision is based on predetermined characteristics of the requests. No exchange of information is needed between FFs or to the central planner. The input for the request selection phase is information on all requests per FF. For each request r_i, consisting of pickup node i and delivery node $i + \sigma$, the information in Table 5.1 is known to the FF:

Table 5.1: Information needed for the request selection phase.

Parameter	Description
$[e_{i+\sigma}, l_{i+\sigma}]$	Time window of the delivery
$D_{i+\sigma}$	Location of the delivery

Most existing request selection methods are based on a fitness function for the requests. Each request is evaluated by this fitness function which results in a fitness score. The requests with the highest fitness score are kept by the freight forwarder and the requests with lower scores are offered to the auction pool. Some of these selection strategies focus on selecting individual attractive requests and others on sets of attractive requests (Gansterer and Hartl, 2016), (Schopka and Kopfer, 2017), (Berger and Bierwirth, 2010). In literature, the fitness score is often based on one or a combination of the following characteristics of the request(s):

1. Marginal profit: The extra profit obtained by handling a request.
2. Request revenue: The revenue obtained when delivering a request.
3. Distance between requests: How close is a set of requests clustered to each other.
4. Distance between request(s) and depot locations: How close is a request to other FF or GH locations.

Studies have shown that selecting requests based on profit or revenue only is not the most effective way for collaboration purposes. When a request is not profitable for one freight forwarder, chances are high that that same request is also not profitable for others. When taking into account the distances between requests, or between requests and depots, the collaboration gain is increased. (Gansterer and Hartl, 2016)

For the coopetition to be successful, the fitness function should be based on a characteristic that can make a request unattractive for one FF yet attractive for another. In the landside air cargo supply chain such a characteristic is the location of the delivery combined with the time window in which the request needs to be delivered at that GH. For example: a FF may have to deliver three requests at GH1 within similar time windows and two requests at GH2 at completely different time windows. The three requests with a similar delivery time window are more attractive for this FF to keep. Furthermore, there is a chance that the other two requests are attractive for other FFs of the consortium. A graphic of this example is shown in Figure 5.2.

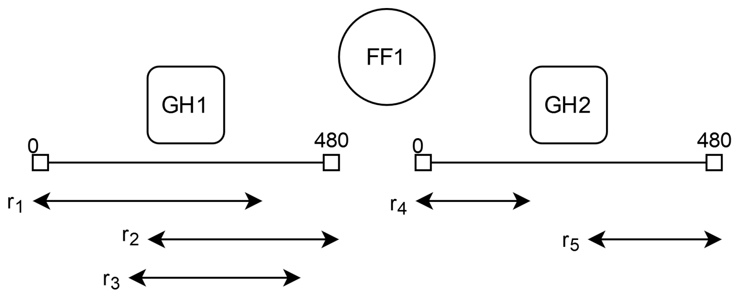

Figure 5.2: Example of request selection. Time horizon is 480 minutes.
Arrows represent delivery time windows of the requests.

The similarity of two time windows is determined by the amount of overlap they have. The amount of overlap between node i and node j (o_{ij}) is calculated with equation 5.1. The amount of overlap between three or more nodes ($o_{i,j,\cdots,m,n}$) with time windows is calculated with equation 5.2.

$$o_{ij} = o_{ji} = \max(0, \min(l_i, l_j) - \max(e_i, e_j)) \tag{5.1}$$
$$o_{i,j,\cdots,m,n} = o_{n,m,\cdots,j,i} = \max(0, \min(l_i, l_j, \cdots, l_m, l_n) - \max(e_i, e_j, \cdots, e_m, e_n)) \tag{5.2}$$

In this project three fitness functions were considered. All three are based on the amount of overlap the delivery of a request has with other request deliveries. For each FF the requests are sorted on delivery location. All delivery nodes with pick up at FF f and delivery at GH g are denoted by $\mathcal{B}^{\mathcal{G}}_{fg}$. The total overlap an individual delivery node (o_i) has with all other requests in $\mathcal{B}^{\mathcal{G}}_{fg}$, is calculated with equation 5.3. The total overlap of a set of delivery nodes (o_S) is calculated with equation 5.4.

$$o_i = \sum_{j \in S} o_{ij} \quad \forall i \neq j \tag{5.3}$$
$$o_S = \sum_{i \in S} \sum_{j \in S} o_{ij} \quad \forall i < j \tag{5.4}$$

Example 5.1 *FF1 has to deliver the requests summarised in Table 5.2. To clarify the notation: request 1 consists of pick-up node 1 and delivery node 13, which also shows that $sigma = 12$. The delivery nodes are divided into two subsets: nodes $13, 14, 15 \in \mathcal{B}^{\mathcal{G}}_{11}$ and $16, 17, 18 \in \mathcal{B}^{\mathcal{G}}_{12}$ The overlap of all nodes within a subset is calculated with equations 5.1 to 5.4.*

Table 5.2: Example delivery data FF 1.

request	*node*	*Type*[a]	*FF*	*GH*	*e_i*	*l_i*
1	*13*	*1*	*1*	*1*	*300*	*480*
2	*14*	*1*	*1*	*1*	*160*	*340*
3	*15*	*1*	*1*	*1*	*300*	*480*
4	*16*	*1*	*1*	*2*	*300*	*480*
5	*17*	*1*	*1*	*2*	*100*	*280*
6	*18*	*1*	*1*	*2*	*100*	*280*

$\mathcal{B}^{\mathcal{G}}_{11}$

$$\begin{aligned}
o_{13,14} &= \max(0, \min(480, 340) - \max(300, 160)) = \max(0, 340 - 300) = 40 \\
o_{13,15} &= \max(0, \min(480, 480) - \max(300, 300)) = \max(0, 480 - 300) = 180 \\
o_{14,15} &= \max(0, \min(340, 480) - \max(160, 300)) = \max(0, 340 - 300) = 40 \\
o_{\mathcal{B}^{\mathcal{G}}_{11}} &= 40 + 180 + 40 = 260 \qquad \textit{(Overlap as a set)} \\
o_{13,14,15} &= \max(0, \min(480, 340, 480) - \max(300, 160, 300)) \\
&= \max(0, 340 - 300) = 40 \qquad \textit{(Overlap as a group)} \\
o_{13} &= 40 + 180 = 220, \quad o_{14} = 40 + 40 = 80, \quad o_{15} = 180 + 40 = 220 \qquad \textit{(Individual overlap)}
\end{aligned}$$

$$
\begin{aligned}
&\mathcal{B}_{12}^{\mathcal{G}} \\
o_{16,17} &= \max(0, \min(480, 280) - \max(300, 100)) = \max(0, 280 - 300) = 0 \\
o_{16,18} &= \max(0, \min(480, 280) - \max(300, 100)) = \max(0, 280 - 300) = 0 \\
o_{17,18} &= \max(0, \min(280, 280) - \max(100, 100)) = \max(0, 280 - 100) = 180 \\
o_{\mathcal{B}_{12}^{\mathcal{G}}} &= 0 + 0 + 180 = 180 \qquad \textit{(Overlap as a set)} \\
o_{16,17,18} &= \max(0, \min(480, 280, 280) - \max(300, 100, 100)) \\
&= \max(0, 280 - 300) = 0 \qquad \textit{(Overlap as a group)} \\
o_{16} &= 0 + 0 = 0, \quad o_{17} = 0 + 180 = 180, \quad o_{18} = 0 + 180 = 180 \qquad \textit{(Individual overlap)}
\end{aligned}
$$

Based on the overlap calculations the following selection criteria were considered:

1. For each FF, keep the requests that individually have the highest amount of total overlap (o_i). In Example 5.1 this would be the requests with delivery nodes 13, 15, 17 and 18.

   a Advantage: Keeping the requests with the most overlap individually ensures flexibility for the next phases in the system.
   b Shortcoming: The kept requests do not necessarily have a high amount of overlap with the other kept requests. In the example delivery nodes 13 and 17 do not have any overlap, their destinations differ.

2. For each FF, keep the requests that have the highest amount of overlap as a group ($o_{i,j,\cdots,m,n}$). In Example 5.1 this would be the requests with delivery nodes 13,14 and 15.

   a Advantage: Requests are chosen as a group, which ensures that shortcoming 1b does not occur.
   b Shortcoming: The worst overlap between any two of the time windows determines the outcome of equation 5.2. In the example node 16 and 17 have no overlap. Even if there were ten more requests with a high overlap amount with for instance node 18, the outcome would still remain zero.

3. For each FF, keep the requests that have the highest amount of overlap as a set (o_S). In Example 5.1 this would be the requests with delivery nodes 13,14 and 15.

   a Advantage: Requests are chosen as a group without shortcomings 1b and 2b.
   b Shortcoming: There may be requests in the chosen set which have minimal to no overlap with the other requests. Because the other requests form such a good set, these 'outliers' also get selected without adding anything to the overlap of the set.

In this project a combination of method 3 and 1 is chosen that encompasses the best features of all three methods and avoids the shortcomings. First, method 3 is applied to select the initial set of requests to keep. Then the total overlap of each individual request (o_i) in this set is evaluated against a preset minimum. If the request does not meet the preset minimum, it will be put into the auction pool. Selection of the best set continues until the threshold, a percentage that dictates the minimum amount of requests the FF wants to keep, is met. All requests that are not selected are put into the auction pool. An example of this procedure is given in Example 5.2.

Example 5.2 *(continues on example 5.1)*
FF1 wants to keep at least half of the requests, setting the threshold to 50%. *The preset minimum amount of overlap for an individual request is* 60 *minutes. With method 3 requests* 13,14 *and* 15 *are selected. All three selected requests comply with the preset minimum overlap and are kept by the FF. Three out of six requests are selected which is equal to the threshold of* 50%. *Requests* 16,17 *and* 18 *are put into the auction pool.*

5.2. Request bundling

Once each FF has decided which requests to keep, each FF communicates to the central planner which requests are put into the auction pool. The set of requests in the auction pool is denoted by $\mathcal{A}$. FFs do not share information on their routing or their capacity constraints with the central planner in this phase. The central planner only needs to know the location and the time window of delivery of all requests in the auction pool. Thus, the central planner determines the bundles under limited information. No information exchange between FFs is required for this phase. The central planner receives an overview of all requests that are put into the auction pool with the following information:

Table 5.3: Information needed for the request bundling, provided by FF to central planner.

Parameter	Description
$[e_{i+\sigma}, l_{i+\sigma}]$	time window of the delivery
$D_{i+\sigma}$	location of the delivery

In literature it is common to generate bundles based on all possible combinations of the requests in the auction pool. For instance if there are three requests $(1,2,3)$ in the auction pool, there would be seven bundles: (1), (2), (3), $(1,2)$, $(1,3)$, $(2,3)$, $(1,2,3)$. The general equation for for this amount is $2^n - 1$, with n the number of requests in the auction pool. From a practical point of view, offering all possible bundles to the FF is computationally too expensive, this will become more clear in the bidding phase. Therefore, it is important to limit the amount of offered bundles, without excluding the most beneficial bundles for the system.

To determine the characteristics of good bundles it is necessary to look ahead to the reassignment of bundles to FFs. In phase four of the auction system each FF is assigned one or no bundle. Therefore, the number of bundles that are reassigned is always less or equal to the number of FFs ($N_{\mathcal{F}}$). Because each request can only be assigned to one FF, the objective of the bundling phase could also be seen as finding promising partitions of the auction pool. The partitions consist of at most $N_{\mathcal{F}}$ bundles. The collection of bundles is denoted by $\mathcal{D}$, which is initially an empty set.

Example 5.3 *There are three FFs who (together) put ten requests into the auction pool,* $\mathcal{A} = (1,2,\cdots,10)$. *Possible partitions of the auction pool would then be:*

$$\begin{array}{ll} a. & (1,2,3) \quad (4,5,6) \quad (7,8,9,10) \\ b. & (1) \quad (2) \quad (3,4,5,6,7,8,9,10) \\ c. & (1,2,3,4,5) \quad (6,7,8,9,10) \end{array}$$

The following points are suggestions for bundle criteria to select promising bundles:

1. Requests in the same bundle have the same delivery location.
2. Requests in the same bundle have a high amount of overlap at a GH location.
3. A bundle in itself is only promising if the rest of $\mathcal{A}$ is partitioned into at most $N_{\mathcal{F}} - 1$ promising bundles.

Example 5.4 *Assume* $\mathcal{A} = (1,2,\cdots,10)$.
An example of a bundle that does not meet criteria 3:
Assume that bundle $b_1 = (1,2,3) \in \mathcal{D}$ *is a promising bundle according to criteria 1 and 2. If in* $\mathcal{D}$ *there are no bundles that form a partition of the rest of the requests,* b_1 *is no longer a promising bundle. Bundle* b_1 *needs other bundles in* $\mathcal{D}$ *to form a partition of (4,5,6,7,8,9,10). For instance, (4,5,6) and (7,8,9,10).*

The following steps are executed to add promising bundles to $\mathcal{D}$. Bundles are only added if they are not yet included in $\mathcal{D}$.

A. All requests in $\mathcal{A}$ are sorted by their delivery location: $\mathcal{A}_g^{\mathcal{G}}$ = requests in the auction pool with delivery at GH g. The first sets of requests that are added to $\mathcal{D}$ are $\mathcal{A}_g^{\mathcal{G}}$ $\forall g \in \mathcal{G}$. These bundles form a partition of the auction nodes that comply with criteria 1 and 3. (Assuming there are more (or equal) FFs than GHs).

B. All requests in $\mathcal{A}$ are sorted by their pickup location: $\mathcal{A}_f^{\mathcal{F}}$ = requests in the auction pool with pickup at FF f = the requests that FF f put into the auction pool. To ensure feasibility of phase 4, the sets of requests $\mathcal{A}_f^{\mathcal{F}}$ $\forall f \in \mathcal{F}$ are added to $\mathcal{D}$. These bundles may not comply with any of the criteria. However, if no better solution can be found, the requests in the auction pool can be returned to their original FF.

C. All requests in $\mathcal{A}$ are sorted by their pickup and delivery location: $\mathcal{A}_{fg}$ = requests in the auction pool with pickup at FF f and delivery at GH g. The $\mathcal{A}_{fg}$ comply with criteria 1 and are added to $\mathcal{D}$. However, they do not necessarily comply with criteria 3. As can be seen in Example 5.5.

   Example 5.5 *Assume* $\mathcal{A} = (1, 2, \cdots, 10)$ *and there are 2 FFs and 2 GHs.*
   Assume: $\mathcal{A}_{11} = (1, 2, 3)$, $\mathcal{A}_{12} = (4, 5, 6)$, $\mathcal{A}_{21} = (7, 8)$ *and* $\mathcal{A}_{22} = (9, 10)$.

   $\mathcal{A}_{ij}$ *are not necessarily attractive bundles because there is no guarantee that the remaining requests in* $\mathcal{A}$ *are partitioned into* $N_{\mathcal{F}} - 1 = 1$ *bundle.*

D. The requests per GH in the auction pool ($\mathcal{A}_g^{\mathcal{G}}$) are partitioned into sets of requests that have a high amount of overlap with each other. This partitioning is done with hierarchical clustering, where the resulting clusters can be seen as bundles. Hierarchical clustering allows for choosing the amount of resulting clusters. The number of bundles can be limited, so the next phases do not become computationally too expensive. These type of bundles comply with criteria 1 and 2. If $\mathcal{A}$ is partitioned into many small bundles, such as in Example 5.5, these bundles do not comply with criterion 3.

With hierarchical clustering each request starts in its own cluster, pairs of clusters are sequentially merged based on their distance until all requests are in one cluster. Requests that are closer to each other get merged first. Therefore, hierarchical clustering requires a type of metric to determine the distance between two requests and a linkage criteria to determine the distance between sets of requests. More about hierarchical clustering can be found in (Johnson, 1967). In this project requests are clustered based on their overlap in delivery time windows. Requests that have more overlap with each other get merged first. The amount of overlap is a measure of closeness and not of distance. Below is explained how to transform the closeness into distance.

For each $\mathcal{A}_g^{\mathcal{G}}$ an overlap matrix is build in the following way: For all requests $r_1 \cdots r_n$ in $\mathcal{A}_g^{\mathcal{G}}$, calculate the amount of overlap between all pairs of requests with equation 5.1. The overlap of a request with itself is defined as zero ($o_{r_a,r_a} = 0$). Then the maximum amount of overlap between any two requests is calculated: $m = max(o_{r_a,r_b})\ \forall r_a, r_b \in \mathcal{A}_g^{\mathcal{G}}$.

$$\begin{pmatrix} o_{r_1,r_1} & o_{r_1,r_2} & \cdots & o_{r_1,r_n} \\ o_{r_2,r_1} & o_{r_2,r_2} & & \vdots \\ \vdots & & \ddots & \\ o_{r_n,r_1} & \cdots & & o_{r_n,r_n} \end{pmatrix} \tag{5.5}$$

Matrix 5.5 can be seen as the closeness matrix of $\mathcal{A}_g^{\mathcal{G}}$. To transform this matrix into a distance matrix the entries of the closeness matrix are subtracted from the maximum of the entire matrix. The entries on the diagonal are set to zero. This results in the distance matrix 5.6.

$$\begin{pmatrix} 0 & m - o_{r_1,r_2} & \cdots & m - o_{r_1,r_n} \\ m - o_{r_2,r_1} & 0 & & \vdots \\ \vdots & & \ddots & \\ m - o_{r_n,r_1} & \cdots & & 0 \end{pmatrix} \tag{5.6}$$

The metric used in this project is: $d(x_a, x_b) = m - o_{x_a,x_b}$. The linkage criterion used in this project is complete-linkage clustering: $min\{d(x_a, x_b) : x_a \in \text{cluster}A, \quad x_b \in \text{cluster}B\}$. This can be seen as: the distance between two sets of requests is based on the distance between the two requests, one in each set, that are the farthest apart. This linkage criterion is similar to the calculation of the overlap of a group of requests ($o_{i,j,\cdots,m,n}$), as explained in Section 5.1.

For the bundles produced with steps A to D, the main problem with complying to criterion 3 is that $\mathcal{A}$ is partitioned into too many bundles. To solve the compliance to criterion 3 for steps C and D, the partition needs to exist out of $N_{\mathcal{F}}$ bundles. Therefore, some bundles are combined to form new bundles, those are $\mathcal{A}_g^{\mathcal{G}}$. A combination of two bundles is simply a bundle that contains all requests from both bundles. It is possible that there are more beneficial ways of combining bundles. However, to keep the amount of bundles small, a combination method is chosen that does not add too many bundles, namely $\binom{N_{\mathcal{G}}}{2}$ bundles.

5.3. Bidding

After selecting promising bundles in the previous phase, the central planner offers the bundles to the FFs for auction. The bidding by the FFs is based on a predetermined method. Which means that if a FF chooses to enter the auction system, they agree upon using this predetermined method for the bidding. The bids are not based on the intuition or greed of the FFs, but on a fair mathematical approach without favouritism. The bidding is done from the perspective of every FF, hence it is a decentralised process. No exchange of information between FFs is needed. In Table 5.4 all required information received from the central planner is shown.

Table 5.4: Information provided from the central planner to the FF for the bidding.

Parameter	Description
$[e_i, l_i]$	Time window of the pickup
P_i	Location of the pickup
$[e_{i+\sigma}, l_{i+\sigma}]$	Time window of the delivery
$D_{i+\sigma}$	Location of the delivery
$y_i = y_{i+\sigma}$	Type of the node[b]
$q_i = q_{i+\sigma}$	Weight of node/request i
$z_i = z_{i+\sigma}$	Width of node/request i
d_{ij}	Distance between node i and j

[b] 0 = pickup, 1 = delivery

It is imaginable that a FF does not want to handle certain types of requests. It is possible to incorporate this into the model by allowing the FF not to bid on that bundle. However, to ensure maximal flexibility of the solution, it is assumed that every FF bids on every offered bundle. Only if a FF is not capable of handling a certain bundle, they do not bid on that bundle.

The bids in the combinatorial auction are based on the marginal profits of a FF for handling the requests in the bundles. The marginal profit of handling bundle b for FF f is defined as the profit with bundle b minus the profit without bundle b, the latter being the same as the profit of only handling the kept requests, see request selection phase in Section 5.1. The profit of handling a set of requests is determined by the revenue a FF obtains from the shipper minus the costs of handling those requests. As mentioned before, FFs keep their initial revenue. However, the cost of serving the requests is not known yet. To determine the costs of handling a set of requests a routing problem must be solved. In this project the routing problems are solved with the meta heuristic discussed in Section 3.4. The output of the meta heuristic is: The cost of the routes, the routes of the trucks, and the arrival and departure times at each node for each truck. For each bundle, two routing problems must be solved:

1. FF f calculates the cost of handling bundle b ($cost_{with}^{fb}$) by solving the routing problem with the kept requests and the bundle requests.
2. FF f calculates the costs of only handling the requests that they kept ($cost_{kept}^{f}$) by solving the routing problem with only the kept requests.

The extra cost of handling bundle b for FF f is called the marginal cost: the cost of handling the kept requests with the requests in the bundle minus the cost of only handling the kept requests ($cost_{with}^{fb} - cost_{kept}^{f}$). The FFs communicate the marginal costs of all bundles to the central planner. Notice that the FF does not communicate the cost or profit of their initial route planning nor their initial revenue.

The central planner can then calculate the marginal profit of handling bundle b for FF f (mp_{fb}). Again it is important to note that revenue is not reallocated between the FFs nor is extra revenue created. Thus, the marginal revenue is zero. That means that the only way the auction coopetition can create extra profit for all FFs is to reduce the total transportation costs. Therefore, marginal profit can be expressed with the following equation:

$$\begin{aligned} mp_{fb} &= \text{marginal revenue - marginal cost} \\ &= 0 - (cost_{with}^{fb} - cost_{kept}^{f}) \\ &= -(cost_{with}^{fb} - cost_{kept}^{f}) \\ &= -\text{marginal cost of handling bundle b for FF f} \end{aligned} \tag{5.7}$$

The bid on bundle b from FF f is set as the marginal profit. The central planner constructs a bid matrix based on the marginal profits of the FFs, where N_b denotes the number of bundles.

$$MP = \begin{pmatrix} mp_{1,1} & mp_{1,2} & \cdots & mp_{1,N_b} \\ mp_{2,1} & mp_{2,2} & & \vdots \\ \vdots & & \ddots & \\ mp_{N_{\mathcal{F}},1} & \cdots & & mp_{N_{\mathcal{F}},N_b} \end{pmatrix} \tag{5.8}$$

The amount of routing problems that need to be solved is $N_{\mathcal{F}} * (N_b + 1)$. This shows why it is important to keep the number of bundles limited.

5.4. Winner determination problem

The central planner calculates the optimal reallocation of the bundles based on the bids of the FFs. The required input for the winner determination problem (WDP) is shown in Table 5.5. The central planner is also informed about the number of docks the GHs have reserved for the participants of the collaboration: $N_{\mathcal{D}}^{g}$ = number of docks available at GH g, which is set to 1 in this project. The outcome of the WDP is a bundle to FF assignment that maximises the total system's marginal profit. For example, if bundle b is assigned to FF f this is denoted as $x_{fb} = 1$.

Example 5.6 *Assume there are 2 FFs and* $\mathcal{A} = (1, 2, \cdots, 10)$.
$\mathcal{D} = (b_1, b_2, b_3, b4)$ *where* $b_1 = (1, 2, 3, 4)$, $b_2 = (5, 6, 7, 8)$, $b_3 = (9, 10)$, $b_4 = (5, 6, 7, 8, 9, 10)$
A possible bundle to FF assignment is b_1 *to FF1 and* b_4 *to FF2. Notation:* $x_{11} = 1$ *and* $x_{24} = 1$

To also take the dock capacity into account the central planner calculates all dock capacity violations between every bundle to FF assignment. In Table 5.5 all required information for this calculation is shown.

Table 5.5: Information provided from the FF to the central planner for the WDP.

Parameter	Description
mp_{fb}	Bid from FF i on bundle b
rk_f	Routing of only kept requests by FF f
rw_{fb}	Routing of kept requests by FF f with bundle b
tk_f	Corresponding timestamps[a] of only kept requests by FF f
tw_{fb}	Corresponding timestamps[a] of kept requests by FF f with bundle b

[a] Timestamps are the departure and arrival times for each node in the route planning

Each bid is based on a truck routing with corresponding timestamps. Therefore, the central planner now knows at what time every truck arrives at a GH. If in assignment x_{fb} and x_{uv} two trucks arrive at the same GH at the same time, this is a dock capacity violation. The amount of dock capacity violations between assignment x_{fb} and x_{uv} is denoted with: $DC_{fb,uv}$.

The mathematical model of the WDP is formulated based on the paper by Gansterer and Hartl (2016), see Table 5.6 and the mixed integer linear program (equations 5.9 to 5.16).

Table 5.6: Explanation of the notation of the WDP.

Notation	Description
$\pi(MP, \mathcal{D})$	Total marginal profit after solving the WDP.
$\mathcal{D}$	Set of offered bundles, $b \in \mathcal{D}$.
MP	Matrix containing the bids.
mp_{fb}	Bid from FF f on bundle b.
C	Cost associated with a dock capacity violation in the WDP.
$\mathcal{F}$	Set of FF, $f \in \mathcal{F}$.
$\mathcal{R}$	Set of requests, $r \in \mathcal{R}$.
W_{br}	0/1 Parameter indicating whether request r is included in bundle b or not.
Q_{fb}	0/1 Parameter indicating whether FF f submitted a bid for bundle b or not.
$DC_{fb,uv}$	Parameter indicating the number of dock capacity violations between x_{fb} and x_{uv}.
x_{fb}	Decision variable indicating whether bundle b is assigned to FF f.
$k_{fb,uv}$	Decision variable indicating the number of dock capacity violations if there is a dock capacity violation in the bundle to FF assignment. Initially these are all set to 0.

$$\pi(MP,\mathcal{D}) = max \sum_{f} \sum_{b} mp_{fb} * x_{fb} - C * \sum_{f} \sum_{b} \sum_{u} \sum_{v} k_{fb,uv} \tag{5.9}$$

$$\sum_{b} x_{fb} \leq 1 \qquad \forall f \in \mathcal{F} \tag{5.10}$$

$$\sum_{f} x_{fb} \leq 1 \qquad \forall b \in \mathcal{D} \tag{5.11}$$

$$\sum_{f} \sum_{b} x_{fb} W_{br} = 1 \qquad \forall r \in \mathcal{R} \tag{5.12}$$

$$x_{fb} \leq Q_{fb} \qquad \forall f \in \mathcal{F},\ \forall b \in \mathcal{D} \tag{5.13}$$

$$(x_{fb} + x_{uv}) * DC_{fb,uv} - k_{fb,uv} \leq DC_{fb,uv} \qquad \forall f, u \in \mathcal{F},\ \forall b, v \in \mathcal{D} \tag{5.14}$$

$$x_{fb} \in \{0, 1\} \qquad \forall f \in \mathcal{F},\ \forall b \in \mathcal{D} \tag{5.15}$$

$$k_{fb,uv} \in \{0, 1, 2, \cdots\} \qquad \forall f, u \in \mathcal{F},\ \forall b, v \in \mathcal{D} \tag{5.16}$$

The objective function (5.9) maximises the total marginal profit of the entire auction system. Each FF can win at most one bundle (5.10) and each bundle can only be assigned at most once (5.11). Constraint (5.12) ensures that each request is assigned exactly once. A FF can only win a bundle if the FF submitted a bid for the bundle (5.13). Constraint (5.14) regulates that if two bundle to FF assignments are chosen, that have a dock capacity violation, the decision variable k is set to the number of dock capacity violations. If only one of the two assignments is chosen, decision variable k remains zero. (5.15) defines that all x_{fb} are binary and (5.16) defines that $k_{fb,uv}$ is always a natural number. This mathematical formulation can be seen as an extension of the well known set partitioning problem. To guarantee feasibility, the central planner created feasible bundles as mentioned in Section 5.2. The output of the WDP is a bundle to FF assignment, which means that each FF receives an overview of which requests they have to transport. The routing plan for these requests were calculated by themselves with the predetermined meta heuristic from Section 3.4. There are two possible outcomes of the WDP:

1. A bundle to FF assignment that has no dock capacity violations. In this situation, the route planning of each FF is feasible in combination with the route planning of all other FFs. Therefore, the planning can be executed accordingly.

2. A bundle to FF assignment with dock capacity violations. Here, the violations need to be solved. If there are dock capacity violations in the outcome of the WDP, decision variable k shows which bundle to FF assignments cause the dock capacity violations. If for example x_{11} and x_{22} need the same dock at the same time, the $k_{11,22}$ will denote the number of dock capacity violations between this pair. An algorithm finds the exact time and location of the dock capacity violation and tries to shift the timestamps of the arriving trucks in such a way that the routes become feasible. More about this procedure, called the time slack strategy and the departure time adjustment strategy, can be found in Section 3.4. If it is not possible with this procedure to solve the dock capacity violations in the routes, the WDP is called again to find an alternative bundle to FF assignment. This is done by adding an extra constraint to the WDP based on $k_{fb,uv}$. The extra constraint ensures that in the new solution x_{11} and x_{22} can not both be chosen: If $k_{fb,uv} \geq 1$ the following constraint is added to the WDP: $x_{fb} + x_{uv} \leq 1$. This procedure is an iterative approach, as the new bundle to FF assignment may again contain an unsolvable dock capacity violation. If it is not possible to find a feasible bundle to FF assignment within an acceptable amount of iterations (15), the iterative algorithm is stopped and all FFs handle their original requests themselves (reverting back to complete individual planning).

In this project the dock capacity violations are solved in the WDP phase. There are other moments where the dock capacity could be solved. For instance, even before the request selection the delivery time windows of the requests could be adjusted in such a way that all requests get a mutually exclusive time window. Unfortunately, this restricts the entire solution space of the problem unreasonably and would lead to even more sub-optimal solutions. Another option would be to take the dock capacity into account in the request selection and bundling phases. The metaheuristic used for the bidding in this project does take into account the dock capacity, as is explained in Section 3.4. If all requests that go to the same GH are transported by the same FF, the metaheuristic ensures that there is no dock capacity violation at that GH. However, this would simply mean a redistribution of the requests where each FF is assigned all requests that go to one GH. This is no longer an auction coopetition as defined in this project.

5.5. Profit sharing

In this phase the extra profit obtained by the coopetition is distributed among the FFs. This phase is executed by the central planner and it does not require additional information. In this project a new profit sharing mechanism, developed by Gansterer et al. (2019b), is chosen because of the following characteristics:

1. Profit reallocation is fair:
   (a) All FFs make at least the same amount of profit after the auction model compared to the individual situation (individual rationality).
   (b) The contribution to the total collaboration gain is taken into account in the allocation (proportional to contribution).
2. Profit reallocation can be executed with limited information:
   (a) FFs do not have to share their initial or after auction profits with other FFs or the central planner.
   (b) FFs do not have to share their revenue (per request) with other FFs or the central planner.
3. Profit reallocation ensures group rationality.
4. Profit reallocation is computationally manageable.

All necessary information for the profit reallocation is derived from:

1. The bids on the bundles that the FFs are assigned in the WDP. φ_f is defined as the marginal profit for FF f of handling the assigned bundle, i.e. the marginal profit (negative marginal cost) of handling the acquired requests.
2. The bids of the FFs on bundles consisting of their own offered requests. ξ_f is defined as the marginal profit for FF f of the bundle that consists of the requests that were put into the auction pool by FF f, i.e. the marginal profit (negative marginal cost) of handling the FFs initially offered requests.

It can happen that the marginal profit of a bundle is positive, i.e. it costs less money to handle the bundle and the kept requests than handling only the kept requests. However, most marginal profits are negative, indicating that it costs extra money to handle more requests.

Subsequently, the central planner can now establish how much profit each FF will gain, if adhering to the request assignment found in the WDP. For each FF the amount of extra profit is equal to $\vartheta_f = \varphi_f - \xi_f$. This is equal to the marginal profit of buying requests minus the marginal profit for selling requests for FF f. The total extra profit gained by the auction based coopetition is $\Theta = \sum_{f \in \mathcal{F}} \vartheta_f$. This extra profit is distributed among the FFs in the coopetition with profit sharing equation (5.17), which assigns the weighted average of contributed sales and purchases of bundles to each FF.

To ensure individual and group rationality, the sum of the absolute values of the marginal profits is used. The marginal profit for buying requests for the total coopetition is $\Phi = \sum_{f \in \mathcal{F}} |\varphi_f|$, the marginal profit for selling requests for the total coopetition is $\Xi = \sum_{f \in \mathcal{F}} |\xi_f|$.

$$\lambda_f = \frac{\Theta}{2} * \left(\frac{|\varphi_f|}{\Phi} + \frac{|\xi_f|}{\Xi} \right) \tag{5.17}$$

The amount FF f pays to the central planner is equal to $max(0, \vartheta_f)$. Therefore, only if serving the requests in the assigned bundle costs less than serving their initially offered requests, the FF pays the central planner. The total share of the extra profit FF f obtains from the central planner consists of two parts: 1) compensation for extra costs and 2) a share of the total collaboration gain (λ_f). The compensation of a FF is equal to the extra costs made by following the WDP assignment: compensation$_f = -min(0, \vartheta_f)$.

Example 5.7 *An overview of this example is shown in Tables 5.7 and 5.8. There are three FFs: A,B and C. All three FFs are the owners of three bundles in the auction pool. FF A owns bundle a, FF B owns bundle b and FF C owns bundle c. All three FFs get assigned one bundle in the WDP: FF A buys bundle b, FF B buys bundle c and FF C buys bundle a.*

For FF A the marginal profit of serving bundle b is -4 (φ), i.e. FF A has 4 more costs to transport the requests in the assigned bundle than only his kept requests. Additionally, the marginal profit for FF A of serving bundle a, which consists out of requests which were initially offered to the pool by FF A, is -12 (ξ). This means that it would cost FF A 12 more to transport all initially owned requests than only his kept requests. Therefore, by no longer serving all initially owned requests and instead serving the assigned requests by the WDP, FF A has 8 (ϑ) less costs for transport. These savings (ϑ) are payed to the central planner by each of the three FFs.

A FF who has extra costs instead of savings, for example FF C, does not pay anything to the central planner. Instead they are compensated for those extra costs by the central planner. FF C has 3 extra costs for serving the assigned requests by the WDP instead of his initially owned requests. Therefore, the central planner pays FF C 3. The extra profit obtained by the auction is divided among the FFs depending on their contribution to the coalition. In this example FF A contributes most to the coalition by selling requests and FF C contributes most by buying requests.

Table 5.7: Example of the profit sharing mechanism.

FF	*sells bundle*	ξ	*buys bundle*	φ	ϑ	*pay to CP*
A	*a*	*-12*	*b*	*-4*	*8*	*8*
B	*b*	*-8*	*c*	*-3*	*5*	*5*
C	*c*	*-6*	*a*	*-9*	*-3*	*0*
Total		*26*		*16*	*10*	*13*

Table 5.8: Example of the profit sharing mechanism.

FF	*Compensation*	λ *= Extra Profit*	*Pay to FF*
A	*0*	$\frac{10}{2} * \left(\frac{4}{16} + \frac{12}{26}\right) = 3.56$	*3.56*
B	*0*	$\frac{10}{2} * \left(\frac{3}{16} + \frac{8}{26}\right) = 2.48$	*2.48*
C	*3*	$\frac{10}{2} * \left(\frac{9}{16} + \frac{6}{26}\right) = 3.97$	*6.97*
Total	*3*	*10*	*13*

5.6. Verification

The model is verified using a variety of test cases, the first three phases are tested separately. Subsequently, the overall model is verified using the same test cases as used for the first three phases.

The verification is performed on a data instance with 3 FFs and 2 GHs. This instance was chosen because it is small enough to limit the computational time of the verification and it is complex enough for a valid verification. The data instance (3_2_24) can be found in Appendix C. The name of the instance indicates in order: the number of FFs, the number of GHs and the amount of requests in the data instance. The results of the verification can be found in Appendix B. Due to the relatively short duration of this project the verification is limited. Priority was given to the development and modelling phases of the project. Nonetheless, the model passed all performed verification tests.

5.7. Expert judgement

In this section, the expert judgement of D. Brink, head of Airfreight the Netherlands at DHL, is summarised. His opinion on the 5-phase auction model was obtained through personal communication. DHL is a global forwarding company active at Schiphol Airport. They offer door-to-door service for many different types of shipments. For example: same day delivery, economy delivery and special deliveries like perishable goods (DHL). Overall D. Brink thinks that the auction based coopetition model has potential. It is promising to see that the model can improve the profit for all collaborating partners. However, showing the model's benefit with only artificial data is not sufficient. The next step would be to see how well the model performs with real life data. To be able to apply the existing model to a real life situation two hurdles need to be overcome: 1. Real life data from multiple FFs is needed. 2. The model must be adapted to enable real life data as input.

D. Brink mentioned that there are still significant differences between the artificial data used in this project and the actual real world circumstances at Schiphol Airport. One of the biggest differences is that delivery time windows are not equal to three hours in the real world. Loose cargo needs to be delivered at the GHs eight hours beforehand and ULDs four hours. This indicates that the GHs do impose a limit on the latest time the delivery of a shipment can take place. The GHs also impose a limit on the earliest time a delivery may take place. The artificial data in this project has similar time window characteristics, except for the size of the time windows. To apply the model to the Schiphol Airport situation the time windows and the total planning horizon need to be scaled up.

To overcome the differences in the artificial data and real world data the model needs to be flexible. It should be able to handle a high variety of input parameters with many possible values. For instance, a planning horizon of a week and time windows of approximately 2 days. The model is already quite complex and many input parameters can be adapted once the real world values are known. For instance: the time horizon, the size of the time windows, the cost of transportation, the attributes of the shipments. Besides this, there are real world aspects that have not been taken into account in this project. For instance, the operations in the depots or the outsourcing of the transportation to a trucking company.

Some aspects of the model were considered promising by D. Brink. According to him it is acceptable if a FF needs to share information with a central planner, as long as proper arrangements are made, for instance a non disclosure agreement. He also thinks that, in the current work environment of the FFs, it is easier to convince FFs to collaborate if there is no information exchange with direct competitors. In addition to this, all required input for the auction model (for example: shipment weight and shipment width) is already available at the FFs.

6 Results

In this chapter the results of the project are discussed. To simplify the presentation of the results, the three different collaboration types are denoted with their corresponding first letters. Individual planning: **I**, Auction coopetition: **A**, Full collaboration: **F**. In Chapter 3, the methods for modelling the collaboration types are explained. A detailed explanation of the model for the auction coopetition can be found in Chapter 5. First, the three collaboration types are compared on the KPIs, as defined in Section 4.1. Second, the three collaboration types are compared on the performance measures, as discussed in Section 4.2. Finally, this results in a trade-off for the types of collaboration.

6.1. Comparison on collaboration efficiency

All results obtained in this section were computed with the models built in Python 3.7, shown in Appendix D. The WDP is solved to optimality with CPLEX.

6.1.1. ART

In each iteration of the LNS a random removal and insertion strategy are chosen, as explained in Section 3.4. This randomness, among others, causes variation in the amount of time each iteration takes. Therefore, to ensure a valid comparison between the different types of collaboration, the allowed run time for each collaboration type is set to an equal amount of time, for example 30 minutes. This means that for the individual planning each FF has 30 minutes to determine a transportation plan. Each FF is assumed to use the metaheuristic for their own planning. Thus, the total computational time for all individual plannings of all FFs can take up to $N_{\mathcal{F}} * 30$ minutes. For the full collaboration, the entire planning for all FFs is calculated at once, i.e. up to 30 minutes of computational time.

The auction coopetition is slightly different than the other two collaboration types, because it is partially performed by a central planner and partially by the FFs. All phases are executed consecutively. In a real world scenario, phases 1 and 3 would be executed by the participating FFs, phases 2, 4 and 5 are executed by the central planner. However, in this project, all calculations are performed by one party. To make the comparison fair, the allowed run time of phases 1 and 3 are multiplied by the number of FFs that collaborate. For example, if phases 2, 4 and 5 take five minutes of computational time, then there are still 25 minutes left for phases 1 and 3. Because these phases can be executed by separate FFs, each of these FFs now have 25 minutes to execute phases 1 and 3. Therefore, in this example the total computational time of the auction system is equal to, 5 minutes for phases 2, 4 and 5 and $25 * N_{\mathcal{F}}$ minutes for phases 1 and 3, so in total 80 minutes. Hereafter, these 30 minutes of allowed run time in a real world scenario are called the Allowed Run Time (ART).

Notice that the computational time of each of the three collaboration types is equal to or higher than the ART. For the individual planning the computational time is equal to $N_{\mathcal{F}} * ART$. For the full collaboration the computational time is equal to ART. For the auction coopetition the computational time is roughly equal to $N_{\mathcal{F}} * ART$, because the bidding phase (phase 3) is the most time consuming.

6.1.2. Computational results

The three different collaboration types are compared on the KPIs from Section 4.1:

1. Profit (Pr)
2. Distance travelled (Di)
3. Load factor (LF_{we} and LF_{wi})
4. Waiting time for a dock to become available (WT)
5. Amount of trucks (Tr)
6. Amount of truck arrivals at the GHs (TGH)

For the individual planning and the auction coopetition it is possible to show the profit per FF in the results tables. However, for the full collaboration no profit allocation mechanism is specified. Therefore, the extra profit obtained by the full collaboration is not reallocated and can not be shown as a result. Another option would be to distribute the extra profit equally over the participating FFs. However, this would give no extra insight compared to the total profit result.

All parameters are set to their default setting, as defined in Chapter 3. The name of the instance indicates in order: the number of FFs, the number of GHs and the amount of requests in the data instance. The partition of the total amount of requests per FF is shown below the instance name. For example, in instance 3_2_27 there are 3 FFs, 2 GHs and 27 requests in total. Out of the 27 requests, 9 belong to FF1, 11 to FF2 and 7 to FF3, see Table 6.1. In the visualisations of the individual planning and the auction coopetition the colour of the route indicates to which FF this truck belongs: tints of red = FF1, tints of blue = FF2, tints of green = FF3. In the full collaboration the colours are only used to indicate the different trucks, the trucks belong to all (or no) FFs, as specified before. The colours in the 'dock arrival' figures correspond to the colours of the truck routes.

In Table 6.1 the results for the smallest instance can be found for an ART of 10 and 60 minutes. Figures 6.1, 6.2 and 6.3 are visualisations of the individual planning results. Figures 6.4 and 6.5 are visualisations of the auction coopetition results. Figures 6.6 and 6.7 are visualisations of the full collaboration results. Additionally, the full collaboration of the 3_2_27 instance is run with an exact solution method. The incumbent solution found after a six hour run is a total profit of 219. This profit is roughly 8% higher than the solution found with the auction coopetition model after only 10 minutes. This shows that the auction coopetition achieves almost the same result as the best incumbent solution using full collaboration in 6 hours of computational time.

Table 6.1: Results of instance 3_2_27 , I and F are computed with the metaheuristic, A with the auction coopetition.

Instance	ART	Type	Pr	Di	LF_{we}	LF_{wi}	WT	Tr	TGH	Pr per FF
3_2_27	10	I	127	99	68	61	47	7	9	[78, 13, 35]
[9, 11, 7]		A	202	86	67	61	0	7	7	[87, 58, 58]
		F	187	95	93	85	0	5	8	-
	60	I	139	98	78	71	38	6	9	[79, 25, 35]
		A	203	87	67	61	0	7	7	[85, 60, 58]
		F	195	92	93	85	0	5	8	-

As one can see in Table 6.1, the auction coopetition performs best on profit, distance, waiting time and the amount of trucks arriving at the GHs. The load factors of the auction coopetition and individual planning are almost the same, while the full collaboration has much higher load factors. The load factors directly correspond to the number of trucks. For the auction coopetition, the profit increase compared to the individual planning for FF2 stands out. All three collaboration types do improve, yet not significantly, when the ART is increased from 10 to 60 minutes. For both the auction coopetition and full collaboration the waiting time is zero, while this is not the case for the individual planning. Here the effect of a central planner can clearly be seen.

In Figures 6.1 and 6.2 it can be seen that some trucks arrive at the same dock at the same time. This causes a dock capacity violation, so the trucks have to queue. Figure 6.3 shows the results when the dock capacity violations are solved. In the real world that would mean that one truck would have to wait until a dock becomes available. Trucks 1 and 2 belonging to FF1 do not have to queue. Truck 4 belonging to FF2 does have to queue at GH1 and GH2, which partially explains the low profit for FF2 in Table 6.1. Truck 5 belonging to FF3 also has to queue at GH1, which partially explains the relatively low profit for FF3 in Table 6.1.

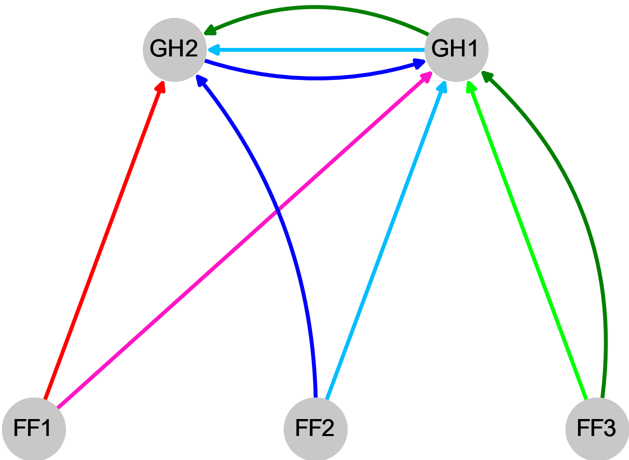

Figure 6.1: Individual planning, routing of the trucks. Instance 3_2_27. ART = 60.

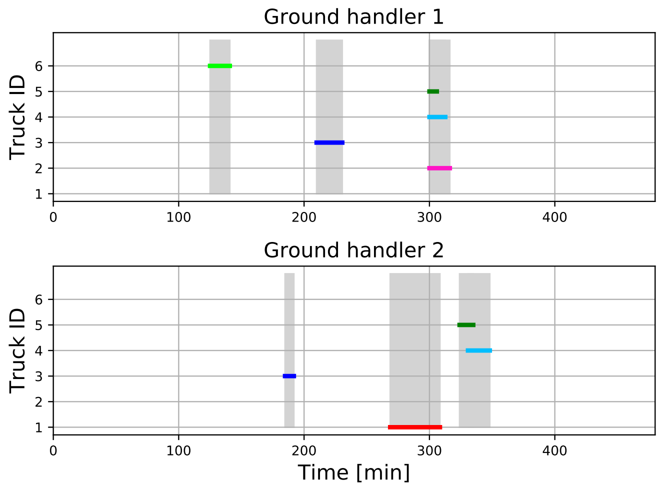

Figure 6.2: Individual planning, truck arrivals at the docks of the GHs without taking the maximum dock capacity of 1 into account. Instance 3_2_27. ART = 60.

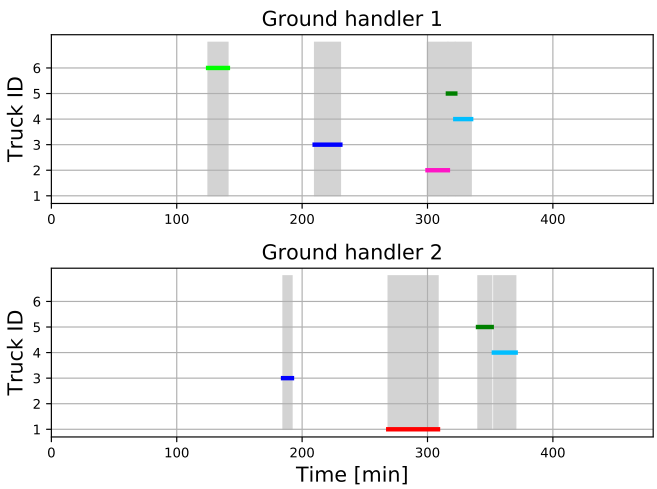

Figure 6.3: Individual planning, truck arrivals at the docks of the GHs. Dock arrivals are shifted because of the maximum dock capacity of 1. Instance 3_2_27. ART = 60.

The profit of the auction coopetition is 46% higher than the profit of the individual planning, while using more trucks. Another main difference can be found in the routing of the trucks. In the individual planning each FF has to visit both GH1 and GH2, which causes three truck movements between the two GHs, as can be seen in Figure 6.1. In the auction coopetition, requests get reassigned to FFs in such a way that there are no movements between the two GHs, as can be seen in Figure 6.4. In the auction coopetition the central planner has information on which truck needs to be at a GH at which time, this information is shared in the bidding phase. Therefore, the central planner can decide to delay a truck at the origin depot, such that there are no two trucks arriving at one GH at the same time, this can clearly be seen in Figure 6.5. Trucks 3 and 2 arrive exactly after truck 4 and 6 are finished with unloading.

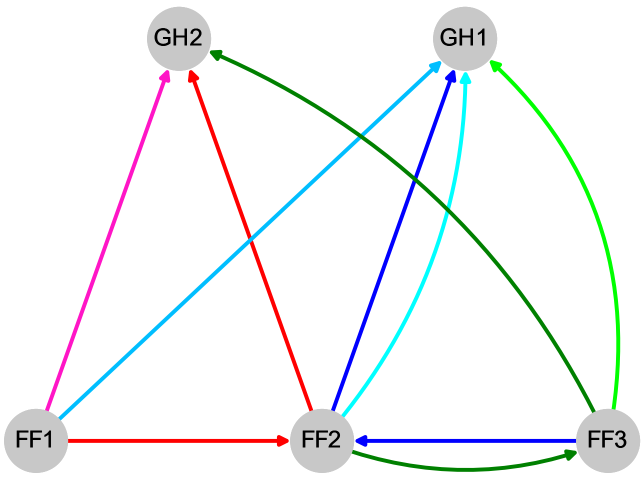

Figure 6.4: Auction coopetition, routing of the trucks. Instance 3_2_27. ART = 60.

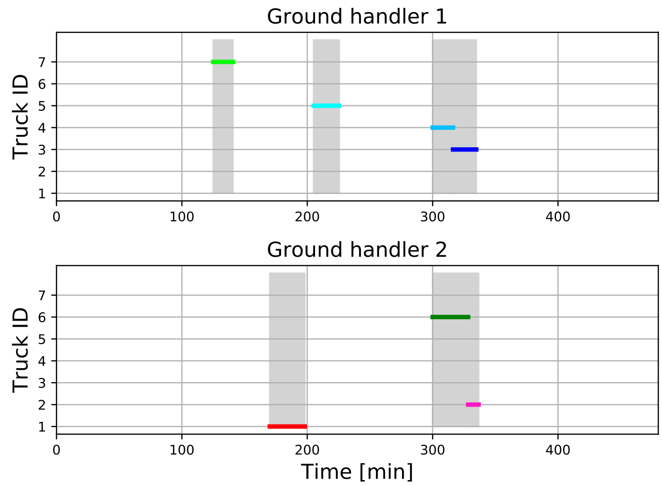

Figure 6.5: Auction coopetition, truck arrivals at the docks of the GHs. Instance 3_2_27. ART = 60.

In the full collaboration the amount of trucks is the lowest. It is interesting to see that there are three truck movements between the GHs and four between the FFs (Figure 6.6). Apparently, the low amount of required trucks is compensated by more truck movements on both sides of the truck planning. Just as in the auction coopetition, the central planner managed to find a solution in which the trucks do not have to queue.

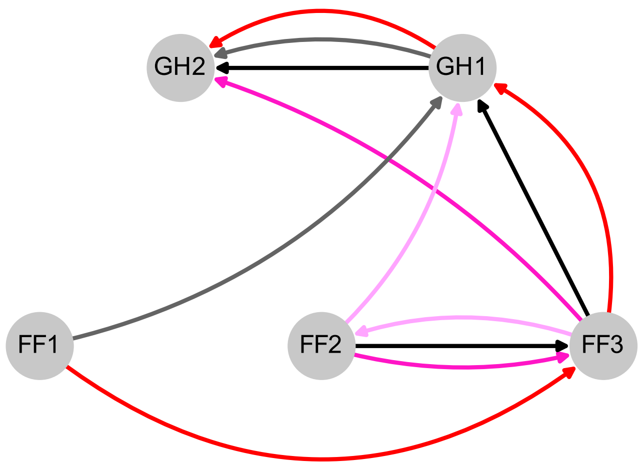

Figure 6.6: Full collaboration, routing of the trucks. Instance 3_2_27. ART = 60.

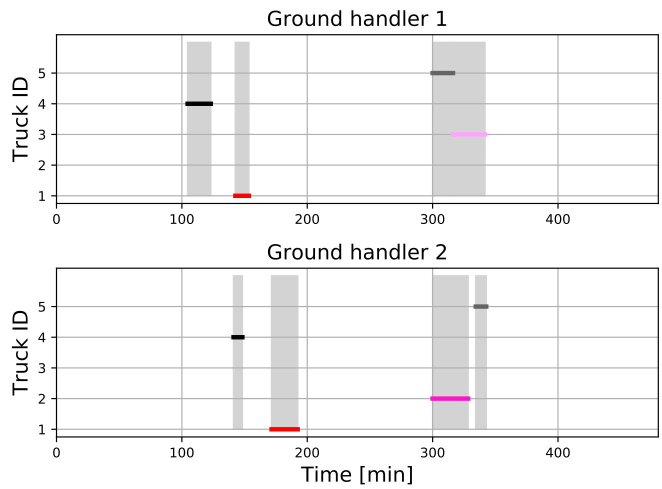

Figure 6.7: Full collaboration, truck arrivals at the docks of the GHs. Instance 3_2_27. ART = 60.

In Table 6.2 the results for the 3_3_30 instance are shown for the ART of 10 and 60 minutes. Figures 6.8 and 6.9 are visualisations of the individual planning results, Figures 6.10 and 6.11 are visualisations of the auction coopetition results, and Figures 6.12 and 6.13 are visualisations of the full collaboration results. Additionally, the full collaboration of the 3_3_30 instance is run with an exact solution method. The incumbent solution found after a six hour run is a total profit of 252. This profit is roughly 7% higher than the solution found with the auction coopetition model after only 10 minutes and roughly 1% higher than the solution found with the auction coopetition model after 60 minutes. This shows that the auction coopetition achieves almost the same result as the best incumbent using full collaboration in 6 hours of computational time.

Table 6.2: Results of instance 3_3_30 , I and F are computed with the metaheuristic, A with the auction coopetition.

Instance	ART	Type	Pr	Di	LF_{we}	LF_{wi}	WT	Tr	TGH	Pr per FF
3_3_30	10	I	150	94	69	66	57	7	12	[49, -24, 124]
[10,6,14]		A	235	79	65	60	0	8	8	[82, 21, 132]
		F	208	94	72	67	0	7	10	-
	60	I	157	94	69	66	53	7	11	[54, -22, 124]
		A	249	71	71	67	0	7	7	[87, 27, 135]
		F	227	82	72	67	0	7	9	-

The auction coopetition performs best on profit, distance, waiting time and the amount of truck arrivals at the GHs. The increase in profit for the full collaboration and auction coopetition, compared to the individual planning, is quite substantial (40-60%). In this instance FF2 has the most benefit from the auction coopetition, turning a loss in the individual planning into a profit. All three collaboration types do improve, but not significantly when the ART is increased from 10 to 60 minutes. The load factors of the auction coopetition slightly increase if the ART is increased from 10 to 60 minutes. This is due to the fact that the routing is performed with one truck less.

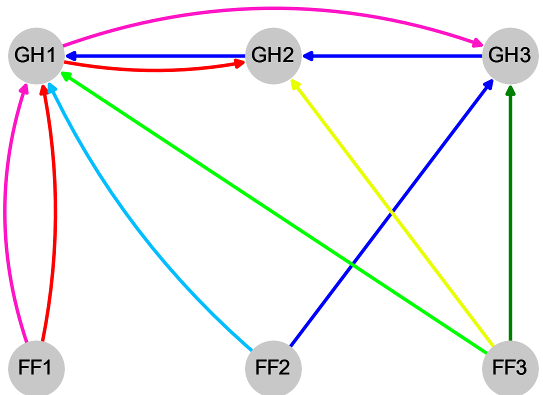

Figure 6.8: Individual planning, routing of the trucks.
Instance 3_3_30. ART = 60.

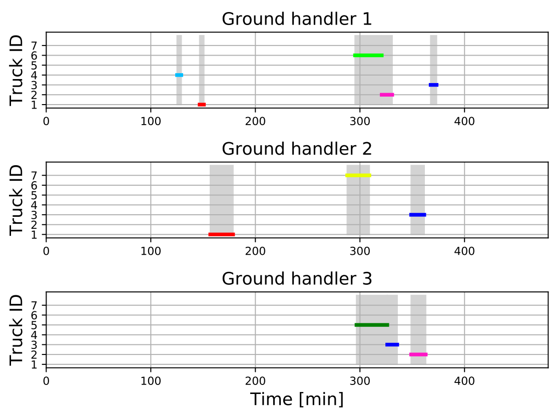

Figure 6.9: Individual planning, truck arrivals at the docks of the GHs.
Instance 3_3_30. ART = 60.

Just as in the individual planning of the 3_2_27 instance, there are a lot of movements between the GHs in the 3_3_30 instance, namely four. In the auction coopetition there are no truck movements between the GHs. Instead, it seems that the trucks move from one FF to another FF to fill up with requests that have to go to the same GH, which results in seven movements between the FFs, as can be seen in Figure 6.10.

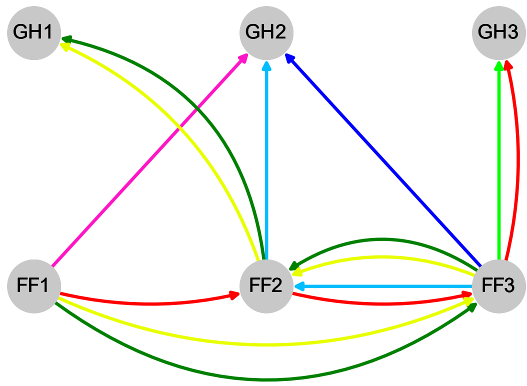

Figure 6.10: Auction coopetition, routing of the trucks. Instance 3_3_30. ART = 60.

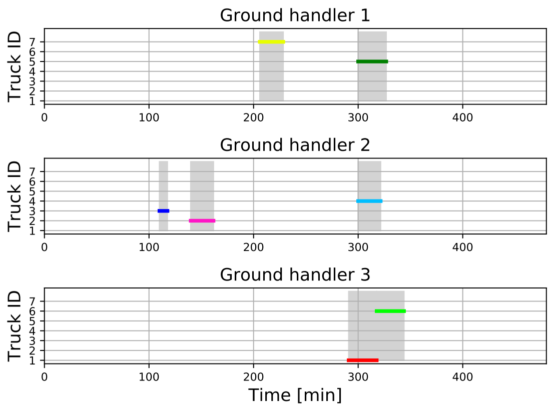

Figure 6.11: Auction coopetition, truck arrivals at the docks of the GHs. Instance 3_3_30. ART = 60.

In the full collaboration the amount of movements between the GHs is only two, while the amount of movements between the FFs is seven, as can be seen in Figure 6.12. In Figures 6.9, 6.11 and 6.13, showing the truck arrivals, it can be seen that the auction coopetition creates the least peak loads for the GHs. Requests that have to go to one GH have been neatly loaded into the same truck. Therefore, at the GHs, there are not many trucks that want to arrive at the same time.

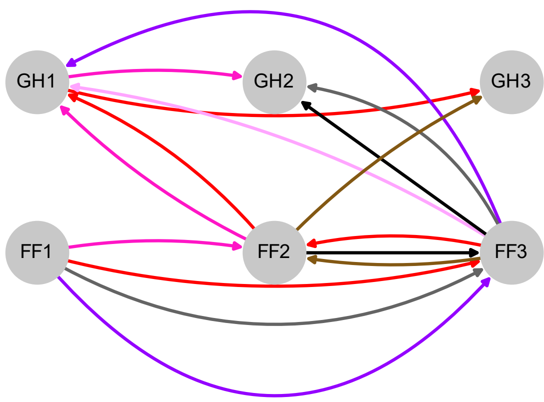

Figure 6.12: Full collaboration, routing of the trucks. Instance 3_3_30. ART = 60.

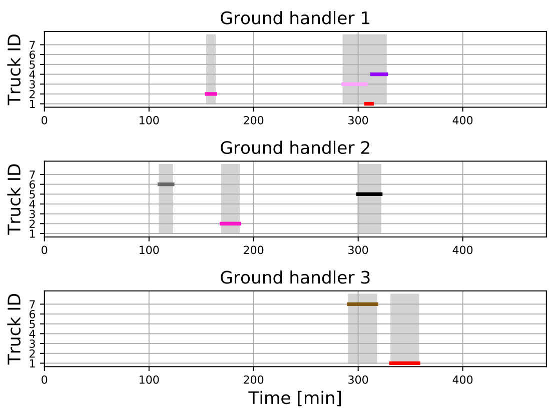

Figure 6.13: Full collaboration, truck arrivals at the docks of the GHs. Instance 3_3_30. ART = 60.

In Table 6.3 the results for the 4_3_50 instance are shown for the ART of 10 and 60 minutes. The auction coopetition performs best on profit, distance, waiting time and truck arrivals at the GHs. Remarkably, in the full collaboration the amount of used trucks goes up when increasing the ART from 10 to 60 minutes, even though the profit increases. Similarly, in the auction coopetition the amount of truck arrivals at the GHs goes up, while the profit increases. These changes could be caused by the fact that the cost of the routing only depends on the total travel time and not on the truck use.

Table 6.3: Results of instance 4_3_50, I and F are computed with the metaheuristic, A with the auction coopetition.

Instance	ART	Type	Pr	Di	LF_{we}	LF_{wi}	WT	Tr	TGH	Pr per FF
4_3_50	10	I	205	142	81	74	172	11	23	[-14, 57, 89, 74]
[12,10,14,14]		A	406	127	74	67	0	12	12	[83, 91, 115, 116]
		F	235	183	87	80	33	10	21	-
	60	I	214	142	81	74	164	11	23	[-15, 43, 81, 106]
		A	424	117	72	66	0	12	14	[99, 90, 117, 117]
		F	246	184	58	53	16	15	24	-

In Table 6.4 the results for the 5_5_98 instance can be found for the ART of 108 minutes. The auction coopetition performs best on profit and truck arrivals at the GHs. The full collaboration performs best on the load factors, waiting time and the amount of used trucks.

Table 6.4: Results of instance 5_5_98, I and F are computed with the metaheuristic, A with the auction coopetition.

Instance	ART	Type	Pr	Di	LF_{we}	LF_{wi}	WT	Tr	TGH	Pr per FF
5_5_98	108	I	254	245	78	72	602	23	43	[129, 104, 53, -120, 87]
[17,23,19,21,18]		A	657	290	81	75	92	22	34	[147, 194, 134, 55, 127]
		F	486	353	85	79	33	21	48	-

6.1.3. Variations in results

The insertion and removal strategies in the large neighbourhood search of the metaheuristic are chosen at random. Therefore, there is a high probability for differences in the solutions of separate runs of the same data instance. It is possible for different runs to result in the same solution if for example in both cases the optimal routing is found, or if both runs result in the same routing by divine intervention. In this section, two data instances are run three times with the same amount of ART. This is not an exhaustive analysis, but it does provide insight in the amount of variation that can occur in the different collaboration types. In Tables 6.5 and 6.6 the results of the variation analysis are shown. The notation is the same as in the previous section.

Table 6.5: Variations in results of instance 3_2_27.

Instance	ART	Type	Run	Pr	Pr per FF
3_2_27	10	I	1	127	[79, 13, 35]
[9,11,7]			2	139	[79, 25, 35]
			3	127	[79, 13, 35]
		A	1	202	[87, 58, 58]
			2	203	[85, 60, 58]
			3	202	[87, 58, 58]
		F	1	187	-
			2	185	-
			3	201	-

Table 6.6: Variations in results of instance 4_3_50.

Instance	ART	Type	Run	Pr	Pr per FF
4_3_50	10	I	1	179	[-25, 46, 79. 78]
[12,10,14,14]			2	205	[-14, 57, 89, 74]
			3	165	[-22, 56, 79, 52]
		A	1	406	[85, 108, 80, 132]
			2	406	[83, 91, 115, 116]
			3	387	[90, 86, 100, 116]
		F	1	287	-
			2	235	-
			3	225	-

As can be seen in Table 6.5, the results for instance 3_2_27 show:
1. For the individual planning the difference in profit from run 1 or 3 to run 2 is 9.4%.
2. For the auction coopetition the difference in profit for the three runs is only 0.5%.
3. For the full collaboration the difference in profit from run 2 to run 3 is 8.6%.

As can be seen in Table 6.6, the results for instance 4_3_50 show:
1. For the individual planning the difference in profit from run 3 to run 2 is 24.2%.
2. For the auction coopetition the difference in profit for the three runs is 4.9%.
3. For the full collaboration the difference in profit from run 2 to run 3 is 27.6%.

The predictability of the individual planning and the full collaboration is quite low. The predictability of the auction coopetition seems to be much higher. Overall the auction coopetition provides the most consistent results across different runs.

6.2. Comparison on collaboration disadvantages

Each of the three different types of collaboration are analysed on how well they perform regarding the collaboration disadvantages, as discussed in Section 4.2. Since the individual planning has no form of collaboration between the FFs, this is set as the benchmark for the other two types of collaboration.

6.2.1. Profit allocation

In Section 4.2.1 two characteristics of a fair profit allocation mechanism are defined: individual rationality and proportionality to contribution. With individual planning there is no redistribution of any profit between the FFs. This complies with both characteristics and therefore it is considered fair. In the auction coopetition the redistribution of the extra profit is done in such a way that every FF is compensated for their possible losses. Hence, individual rationality is guaranteed. The share of the extra profit that is obtained by every FF is determined by their contribution to the coopetition. The FFs can contribute in two ways, by buying or selling requests. Their share in the extra profit is based on the weighted average of their costs for buying and selling requests. Consequently, the profit sharing mechanism defined in this project complies with both characteristics and is considered fair.

Bombelli and Tavasszy (2020) do not specify a profit allocation mechanism for the full collaboration. It is outside of the scope of this project to specify a profit sharing mechanism for the full collaboration setting. However, the profit allocation method for the auction coopetition could also be used in the full collaboration setting. Therefore, in this project it is assumed that the profit sharing mechanism of the full collaboration is at least as fair as the mechanism of the auction coopetition.

6.2.2. Autonomy

In Section 4.2.2 three criteria for the level of autonomy of the FFs are discussed: the amount of decisions made by the FFs, the method of the decisions and from which perspective the decisions are made. In the individual planning, each FF has full authority over all decisions that have to be made. In the auction coopetition several decisions are controlled by the central planner or a predetermined mathematical algorithm.

In the first auction phase, request selection, the FFs need to specify a threshold for the minimum amount of requests they want to keep. In this project this threshold is a percentage. Other options would be to adapt this threshold to an absolute value or to let each FF select specific requests. Both options can easily be implemented in the current model. Although the request selection is based on an algorithm, it is performed in the best interest of the FFs. The most attractive sets of requests are kept by a FF and the least attractive ones are put into the auction pool to be bundled in attractive bundles.

In the second phase, request bundling, no decisions have to be made by the FFs, the bundles are created according to a predetermined algorithm in the best interest of the entire coalition. Although the third phase is executed by the FFs, they do not get to decide the bids on the bundles. The bids are generated by a predetermined mathematical algorithm. In this project it is assumed that each FF bids on every bundle. However, it is also possible to implement a choice for the FFs in this phase, for example the choice of refusing to bid on specific bundles. In phase four a MILP calculates the optimal allocation of the bundles. The FFs do not have any control over this phase and it is performed in the best interest of the entire coalition. The FFs also can not influence the fifth phase, profit allocation, because this is based on a predetermined mathematical equation.

In the full collaboration the autonomy of the FFs is at a minimum. Assuming that all requests of all participating FFs are part of the full collaboration, none of the FFs get to decide which requests to keep. They also do not get the choice to refuse obtaining certain requests from other FFs. The central planner determines which FF gets which requests, the routes, the departure and arrival times and the profit allocation, i.e. the entire transportation planning. Besides this, too many of the practical specifics of the full collaboration are unknown to be able to determine the autonomy. For instance, the choice for a certain profit allocation mechanism could increase the autonomy of the FFs.

6.2.3. Ease of use

The ease of use is defined as the amount of extra actions needed from the FFs to ensure a well functioning auction based coopetition. The individual planning is used as a benchmark. In the auction coopetition, the first extra action is the selection of the requests a FF keeps. This selection is based on a mathematical algorithm and the only input required from the FFs is their threshold value. They can choose to change this threshold value for each new planning or it can automatically be set to the same percentage of the previous planning. Another extra action is generating the bids on the auction pool bundles. These bids are generated by a mathematical algorithm that needs to be run at the FF and requires input from the FF on its cost structure, like fuel cost, the amount of available trucks and driver wages. Once the cost structure of a FF is established, the bids can be generated automatically every time the central planner shares the formed bundles with the FF.

Additionally, the auction coopetition requires five data exchange moments between the FFs and the central planner or vice versa, as shown in Figure 5.1 marked by a $\Diamond$. These data exchanges can be seen as extra actions, if these are not fully automated. Overall, most extra actions concern data exchanges or relatively simple parameter specifications.

The full collaboration also requires extra information exchange actions from the FFs. The central planner requires information on at least the request attributes, like shipment weight, delivery location and delivery time window, to be able to calculate the truck planning for the entire coalition. It could be that the profit allocation of the full collaboration requires additional actions from the FFs, but that has not been specified in this project.

6.2.4. Information sharing

In Table 6.7 an overview of the five information exchange moments of the auction based coopetition can be found. The information exchange moments are denoted with a $\lozenge$ in Figure 5.1. Unless otherwise specified, the information mentioned in Table 6.7 is only required for the requests in the auction pool, not for the requests kept by the FFs. It is important to notice that in the auction based coopetition a FF is not required to share:

1. Their initial price to the shipper for handling a request (revenue per request).
2. Their initial profit or costs.
3. Their initial amount of requests.
4. Their profit of the bundles.
5. Their cost structure.

Table 6.7: Overview of information exchange auction model.

Info $\lozenge$[1]	Direction	Description	Notation
a	FF ⇒ CP	Requests in the auction pool	$r_i \in \mathcal{A}$
		Delivery time window	$[e_{i+\sigma}, l_{i+\sigma}]$
		Delivery location	$D_{i+\sigma}$
b	CP ⇒ FF	Which request is in which bundle	$\mathcal{D}$
		Delivery location	$D_i = D_{i+\sigma}$
		Delivery time window	$[e_{i+\sigma}, l_{i+\sigma}]$
		Pick up time window [2]	$[e_i, l_i]$
		Pick up location [2]	P_i
		Request weight [2]	$q_i = q_{i+\sigma}$
		Request width [2]	$z_i = z_{i+\sigma}$
		Processing time of request i [2]	$p_i = p_{i+\sigma}$
c	FF ⇒ CP	Marginal profit per bundle	$mp_{ij}\ \forall i \in \mathcal{D}, \forall j \in \mathcal{F}$
		Routes and timestamps per bundle	
		Routes and timestamps of only kept requests	
d	CP ⇒ FF	Bundle to FF assignment. Including routes and (updated) timestamps calculated in phase 3.	
e	CP ⇒ FF	Amount of money to pay to or receive from CP	

[1] The $\lozenge$ corresponds to the information exchange moments in Figure 5.1.
[2] This information is made available to the CP by the FFs in information exchange a. Otherwise, the CP would not be able to reveal this information to the other FFs to enable the bidding phase.

6.2.5. Loss of market position

Two ways of losing market position as a FF were identified in Section 4.1:

1. The collaboration type requires FFs to share critical information like the revenue of a shipment.
2. Implicit information can be retrieved from the redistribution of the requests.

Item 1 is not possible in the auction based coopetition system developed in this project, because there is no such information exchange, as can be seen in Section 6.2.4. Item 2 is possible and can occur in different ways:

a. FF2 has a better cost structure than FF1 in general or for specific requests. The probability of FF2 winning those requests in the auction is higher than for other FFs.
b. FF2 has a more flexible transportation network, meaning that a FF has more options to fulfil all his kept and assigned transportation requests.

In this project the cost structures of FFs is the same, therefore option a is not possible. However, option b can occur in the auction coopetition model. This network flexibility is discussed further in Chapter 7.

6.3. Trade-off

The auction coopetition seems to perform the best on several of the transport efficiency KPIs. Especially on the KPIs that are used as indicators for the amount of truck congestion at the GHs, waiting time and the amount of truck arrivals at the GHs. The full collaboration also performs well on the waiting time KPI. The peak loads for the GHs are reduced significantly in the auction coopetition and full collaboration. In the individual planning the waiting times are always the highest, which makes sense, because there is no central planner to avoid the queuing. As mentioned, the waiting time increases the costs for the FFs considerably. Because, in the individual planning, the FFs do not know the planning of the other FFs, it is possible that for one FF the waiting time is so high its profit becomes negative. On forehand, there is no way for the FFs to know if this will occur, which causes uncertainty in their planning and their profit.

Both the decrease in peak loads and the increase in certainty are clear indicators of the added value of a central planner. Both in the auction coopetition and the full collaboration, the amount of total travel time, which waiting time is a part of, for all FFs is minimised. If there is still waiting time remaining in the planning, the associated costs are fairly divided over all collaborating FFs. This increases the certainty for the FFs and their profitability. Therefore, the profit allocation mechanism is considered an advantage of the auction coopetition.

The auction coopetition consistently performs the best in terms of profit. The total profit of the auction coopetition is the highest in every data instance run in Section 6.1. Additionally, the profit per FF seems to be divided more evenly across the FFs compared to the individual planning. Furthermore, the auction coopetition performs quite well in a short ART (10 minutes), where the full collaboration needs more computational time to find an equally good solution. There are some downsides to the auction coopetition. In many of the instances from Section 4.1, the auction coopetition requires the most amount of trucks. This causes the load factors to somewhat decrease, which is a KPI of the environmental impact. On the other hand, the auction coopetition does frequently perform the best on the distance KPI, which is also an environmental impact indicator.

It seems that in the auction coopetition the truck movements on the GH side are exchanged for truck movements on the FF side. To what extent this occurs depends on the specifics of the data instance. This trend is positive in the sense that it alleviates pressure from the dock capacity at the GH side. However, this trend increases the chance of congestion at the FF side. The full collaboration seems to find a middle ground between the movements at the FF and GH sides. The ratio between FF and GH movements could be integrated into the objective function of the auction coopetition. The focus should be on reducing the amount of truck movements on the GH side, while also limiting the amount of movements at the FF side. For example, it could be more attractive to have one movement more on the GH side if this reduces the amount of movements on the FF side significantly.

In the auction coopetition the FFs do lose a part of their autonomy. The amount of decisions they get to make about the requests that are put into the auction pool are limited. For the auction coopetition to work properly each FF needs good insight in their cost structure. This might not be easy to obtain in practice, if the cost structure is not fully known yet. Other than this, the auction coopetition is relatively easy to use for the FFs. Only a very limited amount of information needs to be shared with the central planner, no information needs to be shared with the other FFs. Phase three of the auction is the only phase in which information about costs is shared with the central planner. The type of information that is shared with the central planner only concerns marginal costs and not the initial or total routing costs of a FF. A possible downside of the auction coopetition is the possibility to deduce implicit information about the cost structure of the other FFs, this is discussed further in Chapter 7.

It can be said that, in the full collaboration the FFs lose almost all their autonomy. This is a downside of the full collaboration compared to the auction coopetition, where competition is preserved. Also, it is likely that the ease of use of the full collaboration is comparable to the auction coopetition. On the other aspects there is not enough information at this moment to make a full trade-off for the full collaboration.

7

Discussion

In this Chapter some interesting aspects of the results are discussed in Section 7.1. While good results were obtained in this study, certain limitations are mentioned in Section 7.2.

7.1. Results

In the auction coopetition the KPIs only improve slightly if the ART is increased from 10 to 60 minutes. This could be caused by the fact that the solution space of the auction coopetition is significantly reduced in the earlier phases of the auction. In the selection and bundling phases the amount of possible solutions is significantly restricted. For example, if two requests are never in the same bundle, these requests will always be transported by a different FF. The possible solution where both requests are transported by the same FF is excluded from the solution space. Because the solution space is made smaller, the optimal solution is worse than or equal to the optimal solution of the entire (full collaboration) problem. Finding a decent solution in a significantly restricted solution space is faster than finding a decent solution in the entire solution space. Because the solution space is smaller and a much larger ART does not improve the solution significantly, it can be said that the auction coopetition model is able to find a decent solution within restricted computational time.

Network flexibility is seen as the amount of options a FF has to fulfil all transportation requests. With an increase in, for example, the amount of initial requests (size of a FF), the amount of transportation options increases. As one can see in Section 6.1, the FFs with the highest amount of initial requests generally gain the most from the auction based coopetition. The amount of initially owned requests does not influence the profit allocation mechanism directly. A FF can contribute to the coopetition by buying requests, despite being small and not having many requests to sell. The size of FF may, however, influence prior phases in the auction model and thus influence the profit allocation indirectly by creating better contribution opportunities for bigger FFs (network flexibility). This phenomenon in itself is not a major problem. It makes sense that a FF that can contribute more to the collaboration (regardless of how) also gains more from the collaboration. Network flexibility does become an issue when a FF can retrieve implicit information about the pricing of another FF. For example, if a large FF 1 and a smaller FF 2 start collaborating, there is a chance that, because of higher network flexibility (or a better cost structure), FF 1 consistently wins the bundles containing the requests of FF 2. In that case, FF 1 could choose to undercut FF 2. These aspects of the auction based coopetition might discourage relatively small FFs to join the collaboration.

The difference in the results of the individual planning and auction coopetition seem to be larger than in literature. This could be caused by the following factors:

1. In this project, the dock capacity of the GHs is taken into account, which is a unique feature of this project. This causes a part of the differences (in profit) between the individual planning and auction coopetition. In larger instances this difference further increases because more dock capacity violations occur in the individual planning.

2. The simulated annealing approach (part of the metaheuristic) chosen in this project seems to perform best for the auction coopetition.

3. The solution space of the auction coopetition is much smaller than for the individual planning and full collaboration. Therefore, the individual planning and full collaborations would require more time to find a equally good solution as the auction coopetition.

It is important to note that, the KPI for the amount of trucks does not represent the amount of trucks that is required in practice to fulfil the route planning. If two routes are planned at completely different moments in time, those routes could in practice be driven by the same truck.

7.2. Limitations

The objective of all three collaboration types is to minimise the total transportation time. This means that a solution is only evaluated on the transportation time, while in practice many other aspects of a solution define its potential. The objective function could be adjusted to take into account, for instance, the amount of trucks, distance and the amount of truck arrivals. This is generally done by assigning a weight to each of the parts in the objective function. Then, instead of focusing on finding solutions with a better total transportation time, the other aspects are also taken into account in the evaluation. This way, solutions that may have a low total travel time, but for instance use a lot of trucks, are not seen as good solutions. Additionally, this could increase the efficiency in the exploration of the solution space.

The simulated annealing approach chosen in this project, as explained in Section 3.4, does not seem to perform very well for the full collaboration. The probability of a worse neighbour solution being chosen as the new current solution depends on time instead of the number of iterations. The probability decreases when there is less time left for the entire SA to run. The total time the SA may run is set to the ART, which is 10, 60 or 108 minutes. This causes the probability to accept a worse neighbour solution to be very high in the beginning of the SA. The probability is so high that the solutions improve very slowly until there is not much time left for the SA to finish. This partially explains why the full collaboration KPIs do not improve a lot when ART is increased from 10 to 60 minutes. This partially holds for the individual planning, because the individual planning problems are smaller in terms of number of requests and the planning is made per FF. By adjusting the SA framework to the specific characteristics of the collaboration types, the results could improve.

The large neighbourhood search could be improved by adding an adaptive aspect to the probability of the insertion and removal operators. If an insertion or removal operator performs better than the other, the probability of choosing this operator increases. Wu (2019) already implemented this, but it was not used in this project because initially the amount of runs for the the models was deemed to be too small for the adaptivity to have any effect. Additionally, the insertion and removal strategies could be adjusted to specifically fit the needs of this vehicle routing problem. For instance, the current insertion and removal strategies do not consider dock capacity constraints directly. The 2-regret insertion was found to be the best performing of the insertion methods. This makes sense because the 2-regret insertion calculates the routing results for many possible request insertion options and chooses the best one. Consequently, the 2-regret insertion takes a lot of time to calculate. The other insertion strategies take less time to calculate, but perform worse. This time aspect should be taken into account when implementing an adaptive large neighbourhood search. The increase in probability of choosing a certain operator should be based on the improvement of the results per time unit, rather than only the improvement of the results.

One of the limitations of this project is the fact that it is based on artificial data. The artificial data is largely based on input found in literature, therefore it is deemed quite realistic. However, before concrete statements about a real world situation can be made, an auction based coopetition model should be executed with real world data. This model is a step in the right direction because it does not require large amounts of time to compute a solution for larger instances. Additionally, the model only requires information that is already available at the FFs.

The auction phases in this project were kept relatively simple. Their development was focused on ingenuity and not on optimal performance. Therefore, there is still improvement that can be made in the phases of the auction model. The selection and bundling phases in this study focus mainly on the time windows and their overlap at the GHs. These phases could be improved by taking into account more aspects of the requests. For instance, the request selection could also include the profitability of a request. In practice it could be that a FF is not willing to sell a request that is very profitable. Another example is the bundling of the requests in phase two, this could be improved in a similar way Gansterer et al. (2019b) did. They take into account multiple important aspects of the candidate bundles, like route length and how scattered the request locations are, and they find good bundles with a genetic algorithm.

In this project it is assumed that the collaborating FFs bid truthfully. This means that they communicate their truthful routing costs, found with the metaheuristic, to the central planner. However, in practice a FF might be tempted to communicate an untruthful cost to the central planner. The impact of such untruthful bids is unkown in this study. It is important to investigate what would happen to the overall profit and the profit of the individual FFs if one (or multiple) bid untruthfully. For example, a FF says their costs for a route are higher than the costs the metaheuristic calculated. Would this FF get more compensation for executing this route? Or would none of the bundles get assigned to this FF because of the higher costs? The effects of untruthful bidding in an auction based coopetition model should be investigated. Another possible way that the bids of a FF might not be truthful is when the FF does not know its full cost structure. It would be interesting to see how a variety in cost structures influences the auction coopetition.

8 Conclusion and Recommendations

8.1. Conclusion

The main goal of this project is to show the key effects of introducing auction based coopetition in the landside air cargo supply chain. To show these key effects a comparison between three different types of freight forwarder collaboration is made: individual planning, full collaboration and the auction based coopetition. The collaboration types are modelled using a metaheuristic based on Wu (2019). The maximum allowed run time for the models was set to an equal amount, such that in a real world setting the models would have had the same amount of computational time.

The key effects are divided into transport efficiency advantages and disadvantages of collaboration. Transport efficiency is analysed on six different key performance indicators: profit, distance travelled, load factor, waiting time, amount of used trucks, amount of truck arrivals at the ground handler side.

Overall the auction based coopetition, compared to the other two collaboration types, generally performed best on profit, distance, waiting time, and the amount of truck arrivals. The introduction of an auction based system increased the profit (40-160%) and other transport efficiency KPIs significantly, due to several reasons:

1. The solution space of the auction based coopetition is a lot smaller than the solution space of the other collaboration types. Therefore, the auction coopetition model is able to find a better solution in less computational time.
2. The requests are redistributed among the freight forwarders in such a way that the peak loads at the ground handlers are reduced, which reduces congestion.
3. The central planner has information about the routes of all the freight forwarders. With this information the central planner can adjust the route plannings for all freight forwarders such that the amount of waiting time is minimised.
4. The auction based coopetition is a form of collaboration, which means that the central planner can optimally use each of the freight forwarders transportation options, which reduces the total transportation costs for the coalition.

Additionally, the auction based coopetition was evaluated on five possible disadvantages of collaboration: unfair profit allocation, loss of autonomy, ease of use, the need to share critical company information and the loss of market position.

The profit allocation mechanism of the auction coopetition ensures individual rationality and redistributes the extra profit according to the contribution of a freight forwarder to the total collaboration gain. The mechanism increases the consistency of the profit of a freight forwarder, compared to the individual planning. The fluctuations in profit are partially caused by the unpredictability in the possible queuing at the ground handlers. The central planner in the auction based coopetition is able to minimise the amount of dock capacity violations and therefore minimise the waiting time (queuing). The costs for the remaining waiting time in the planning are fairly shared by all participating collaborators. Therefore, the profit allocation mechanism for the auction based coopetition is seen as an advantage compared to the individual planning, rather than a disadvantage.

The freight forwarders lose part of their autonomy to the central planner in the auction based coopetition. They are allowed to choose the percentage of their initial requests that they want to keep. However, they have limited control over the requests that are put into the auction pool. This does cause the entire system to be relatively easy to use for the freight forwarders, as they do not have perform many extra actions. Lastly, in the auction based coopetition a freight forwarder is only required to share non critical information with the central planner.

The main contribution of this project is twofold. First, the fully integrated five phase auction based coopetition model is a methodological contribution. A unique aspect is the fact that the dock capacity of the ground handlers is taken into account in an auction based model. Also, the developed request selection and bundling procedures are based on the time windows of the request deliveries. Second, the potential of such an auction based coopetition is shown for an air cargo supply chain scenario. There is a clear increase in profitability for the freight forwarders and a decrease in congestion at the ground handlers. Furthermore, the total travelled distance decreases, which indicates a beneficial environmental effect. The data used in this project is artificial. Therefore, it would require more research to establish the real world potential of the auction based coopetition system presented in this project.

8.2. Scientific recommendations

It is interesting to see that the auction based coopetition model consistently finds better solutions than the full collaboration model. Because the solution space of the auction model is much smaller, the speed at which the solution quality increases is higher than with the full collaboration model. A recommendation is to investigate which aspects of the auction model could also be used in a metaheuristic to speed up the search in the full collaboration model and the individual planning. For instance, a sort of bundling approach to find attractive bundles to put into the same truck can be used. When there is limited improvement in the solution quality using this approach, switch to the more flexible version where bundles can be broken up.

Other possible changes or additions to the current auction based coopetition model are discussed in Section 7.2.

In this project the hypothesis is that one of the collaborators could be able to acquire implicit information about the other participants. Another recommendation would be to investigate whether it is possible to acquire implicit information about the pricing of another collaborator/competitor in an auction based coopetition such as in this project. Example questions to be answered are: To what extent could this information be used? How can it be used? Will this have a major impact on the willingness to join such a coopetition?

8.3. Applications

Although the auction based coopetition model developed in this project is quite theoretical, two main applications are identified. First, the model can obviously be used for the air cargo supply chain on any busy airport in the world. Although the results obtained in this thesis are based on realistic artificial data, it is imaginable that freight forwarders want more certainty when considering to implement such an auction based system. Implementing such a big change costs valuable resources and it is imperative to know up front what the return on investment is.

To illustrate the full real world potential, a test case is advised for a group of freight forwarders interested in the implementation of the auction based system. This test case consists out of the following steps. First, the required data for the auction model of a representative time period (for example a week) should be made available by all collaborating freight forwarders to a test central planner. The central planner could for instance be an academic student, one of the freight forwarders or a work-group composed of employees of all collaborating freight forwarders. If the required data is not available for a representative time period in the past, one could choose a representative time period in the future and ensure that all required data is gathered. For this test period the freight forwarders perform the transportation in their usual way according to their individual plannings. It is not possible to actually perform both the individual plannings and the auction coopetition for the same test period in the real world. Therefore, parallel to the execution of the individual plannings, the test central planner should simulate the transportation of the requests according to the auction coopetition for the test period. In this simulation as much data as possible should be taken into account. For instance, if in the test period there is a lot of traffic, which lowers the average speed of the trucks, the average speed of the simulated auction coopetition should also be lowered.

This kind of simulation gives a precise comparison without having to actually perform the transportation according to the auction coopetition model. If the results of the auction coopetition simulation are promising, for example the cost savings exceed the implementation costs, the freight forwarders could choose to run a real world pilot. If the pilot shows that the auction coopetition outperforms the individual plannings, under comparable circumstances, the freight forwarders can choose to fully implement the auction coopetition.

Another possible real world application of the auction coopetition model is last mile delivery of packages and parcels in certain cities. Traffic congestion and car free zones keep increasing in city centres around the world. Partly, this is due to the amount of delivery trucks that drive around in these city centres to deliver packages. The efficiency of such a last mile delivery system could be increased by using an auction based coopetition between the owners of the trucks, for example PostNL, DHL and UPS.

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A

Paper

AUCTION BASED COOPETITION IN THE LANDSIDE AIR CARGO SUPPLY CHAIN

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ABSTRACT

Increased competitiveness with other transport systems and declining operation margins have motivated freight forwarders in the air cargo transport industry to look into horizontal collaboration. This paper focuses on developing a fully integrated five phase auction based coopetition model, a form of horizontal collaboration where competition is preserved. A combinatorial auction is used to exchange transportation requests without having to reveal critical company information. Freight forwarders submit requests into an auction pool, where they are grouped into attractive bundles by a central planner and offered for auction. The request selection and bundling procedures, developed in this paper, are based on the time windows of the request deliveries. A freight forwarder's bid on each bundle is equal to the marginal profit of that bundle, which is obtained by solving two NP-hard routing problems with a simulated annealing and large neighbourhood search metaheuristic. A unique aspect of the auction, is that the dock capacity of the ground handlers is taken into account, which helps to alleviate truck congestion at the ground handlers. The potential of the auction based coopetition model is shown for an air cargo supply chain scenario. There is a clear increase in profitability for the collaborating freight forwarders, because the auction model decreases the transportation costs for the entire coalition. This cost reduction is achieved by an increase in transport efficiency, while the collaboration disadvantages as seen in literature are limited.

Keywords Combinatorial Auction · LTL Planning · Collaboration · Competition · Potential · Congestion · Dock Capacity · PDPTW · Request Exchange

1 Introduction

The increase in demanding consumer lifestyles and the current societal search for sustainability call for an increase in efficiency of logistic service providers. Until now, freight forwarding companies in the air cargo supply chain were able to manage the complexity and competitiveness of the market with high margins, optimisation of their own resources and vertical collaboration. The emergence of integrative services, increased competitiveness with other transport systems and declining operations margins have motivated the air cargo transport industry to look into horizontal collaboration (Ankersmit et al., 2014), (Ferrell et al., 2019). Horizontal collaboration occurs when companies that work at the same level of the supply chain decide to work together, rather than operate separately, with the goal to increase their efficiency.

Freight forwarders (FFs) organise the transportation requests from shippers by finding a routing strategy for their trucks from the freight forwarding depot to the ground handlers (GHs) on the airport. Bombelli and Tavasszy (2020) developed a landside air cargo supply chain problem with pick up and delivery time windows, to model horizontal collaboration between FFs for the transport of air cargo. The collaboration is modelled by assuming that a homogeneous fleet of trucks is shared by all freight forwarders. A central planner, with full information of the collaborating forwarders and all transport requests, computes the optimal routing strategy for the fleet. Wu (2019) developed a meta heuristic for this formulation to decrease the computational time, which poses challenges for medium and large-sized instances. A new addition to the model is that they account for the maximum dock capacity at the ground handler's side. With an increase in shipments it occurs more frequently that the number of arriving trucks exceeds the dock capacity, leading to queuing, which is highly undesirable.

Recent studies show good results in improving reliability, use of resources, sustainability, congestion, costs, travel distance and other system performances (Wu, 2019), (Gansterer et al., 2019b), (Verdonck et al., 2013), (Berger and Bierwirth, 2010). However, the unwillingness of companies to share information is delaying the shift towards more horizontal collaboration (Gansterer et al., 2019a), (Raweewan and Ferrell, 2018). In this paper the potential of an auction based horizontal collaboration system, is analysed, where the system preserves competition between freight forwarders and requires limited information to be revealed. Such a type of collaboration is referred to as auction based coopetition.

Berger and Bierwirth (2010) defined an auction based collaboration system consisting of five auction phases. All cooperating FFs submit transportation requests into a common auction pool. The requests are then bundled and offered for auction. The FFs bid on the offered bundles of transportation requests and the bundles are assigned to FFs based on their bids. In the final step the collected profits are distributed among the FFs.

The contribution of this paper is twofold: (1) A fully integrated five phase auction mechanism is modelled, including dock capacity constraints and a tailored request selection and bundling approach (Methodological contribution). (2) Three different types of collaboration, auction based coopetition, no collaboration and full collaboration, are compared on transport efficiency while keeping track of the possible disadvantages (Assessment of system potential).

2 Methodology

To analyse the key effects of introducing the auction based coopetition a comparison between three types of collaboration is made: Individual collaboration (**I**), Auction based coopetition (**A**) and Full collaboration (**F**). The comparison of the three collaboration types is based on KPIs and other performance measures, as discussed in Section 2.3 and Section 2.4.

The three collaboration types are based on the Multi-Warehouse Dock-Capacitated Pickup and Delivery Problem with Time Windows (MWDC-PDPTW) created by Bombelli and Tavasszy (2020). In this paper the meta heuristic, explained in more detail in Section 2.2, is used as a basis for the solution method of the individual planning and the full collaborattion, as shown in Section 2.1.

The auction coopetition is the main focus of this paper. The five auction phases from Berger and Bierwirth (2010) form the basis for the solution method of the auction coopetition. In this paper all five auction phases are modelled and solved, as shown in Chapter 3. By comparing the auction coopetition to the individual planning and the full collaboration, the potential of the auction based coopetition is determined. An overview of all necessary steps, including their input information, is shown in Figure 1.

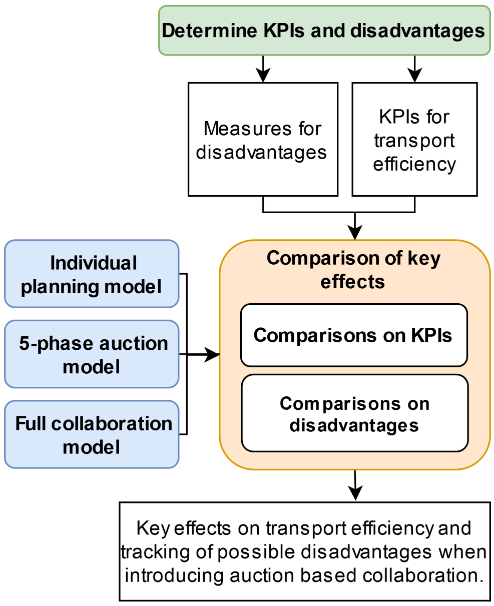

Figure 1: The applied methodology, where the rounded blue boxes indicate the three collaboration models, the rectangular boxes indicate input and output and the rounded boxes indicate processes.

2.1 Problem formulation

In both the auction coopetition and the full collaboration, a consortium of FFs agrees to collaborate, to perform export deliveries to GHs. Each FF has a set of requests that have to be transported from the location of the FF to certain

GHs within a specified planning horizon. At the same time the GHs involved in the initiative agree to reserve a subset of their export docks for trucks belonging to the consortium. The goal of the coalition is to find a more attractive planning solution for all involved parties compared to a non-collaborative scenario. A graphical representation of all three collaboration types can be found in Figures 2, 3 and 4.

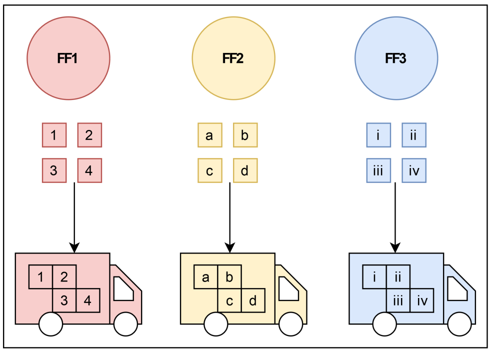

Figure 2: Diagram of individual planning.

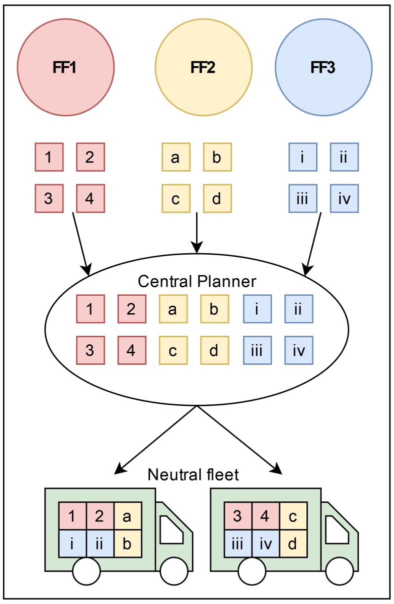

Figure 3: Diagram of full collaboration.

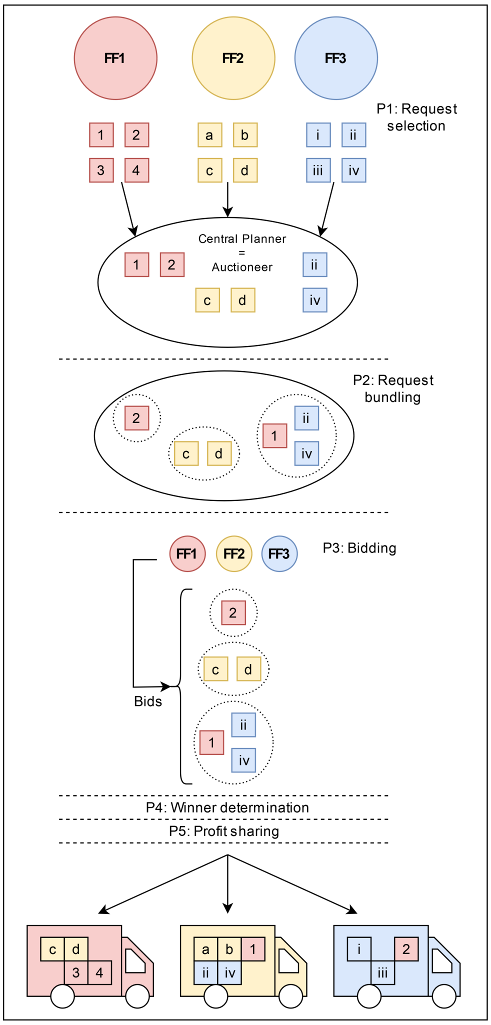

Figure 4: Diagram of auction based coopetition.

In the auction coopetition and the full collaboration a central planner supervises the coalition and defines: (1) a new request allocation, i.e. which FF will handle which request. (2) a routing strategy for each FF, i.e. a sequence of FFs and GHs to visit. (3) a loading strategy, i.e. a sequence of requests to be picked up and then delivered. (4) a dock assignment strategy, i.e. a truck-dock pair for every warehouse visited. Given the size and complexity of the problem, the goal is not necessarily to solve each problem to optimality. Rather, the goal is to demonstrate that by adhering to the rules of the consortium, every FF is more profitable than if it continued to operate as a single entity.

The main difference between the auction coopetition and the full collaboration is the method for assigning requests to the FFs. In the full collaboration the central planner has full information on the shipments of every FF in the coalition. With the metaheuristic based on (Wu, 2019) a request assignment is found such that routing costs are minimised. In the auction coopetition no critical company information is shared with other FFs or the central planner. The central planner also acts as auctioneer for the combinatorial auction. Additionally, the FFs are seen as individual companies that are all responsible for the transportation of their assigned requests. The assignment of the requests to the collaborating FFs is done by means of five integrated auction phases, proposed by Berger and Bierwirth (2010):

1. Request selection by the FFs: Every FF selects requests based on predetermined characteristics to enter in the auction pool.
2. Request bundling by the central planner: The requests in the auction pool are put together in sets to form more attractive sets called bundles.
3. Bidding by the FFs: Each FF bids on the bundles generated in the previous step. A bid is based on the marginal profit for a FF of handling that specific bundle.
4. Winner determination by the central planner: The bundles get assigned to the FFs in such a way that the overall profit for all FFs combined is maximised.
5. Profit sharing for the FFs: The profit gained by the request exchanges is divided among all participating FFs.

In the individual planning each FF defines their routing strategy, loading strategy and dock assignment strategy, not taking into account the requests of the other FFs. In each of the three collaboration types, each request is mapped by two nodes, a pickup node on the FF side and a delivery node on the GH side. All pickup and delivery nodes are characterised by a time window $[e_i, l_i]$, which means that each request must be handled within a finite time frame. It is assumed that all requests are consolidated at the FFs or upstream in the supply chain. Therefore, trucks are only moving unit load devices (ULDs). The dock capacity is only considered on the delivery side of the problem, i.e. there is one dock available at each GH. This assumption is justified, because GHs are generally the bottleneck in the landside air cargo supply chain. In addition, two restrictions that are specific to the air cargo supply chain are added. (1) To ensure an efficient loading strategy for the trucks, all pickups precede all deliveries in a truck tour. (2) To model rear-loading of the trucks and to avoid unnecessary unloading at intermediate GHs, deliveries are carried out in reverse order with respect to pickups in a Last-In-First-Out (LIFO) approach. This requirement is especially crucial because in this paper the ULDs occupy most of the lateral space in the trailers.

2.2 Metaheuristic

The metaheuristic is based on a simulated annealing framework. In each iteration of the SA framework a new neighbour solution is found with a Large Neighbourhood Search (LNS). The LNS generates a new solution $S*$ from the current solution S_c by removing requests from a route and then inserting requests into a route (Wu, 2019). The cost (J) of a solution (S) is determined by the total amount of time it takes to deliver all requests to the GHs (TTT_S) and a predetermined transportation cost per time parameter (c_τ): $J(S) = c_\tau * TTT_S$. The objective of the meta heuristic is to find a routing solution with the least amount of costs and thus the least amount of total transportation time. Additional costs are added to the objective function if the solution is infeasible.

Part of the input of the meta heuristic is the set of requests that need to be shipped. By adjusting the set of shipments the meta heuristic can be used to calculate the full collaboration costs and the individua planning costs. To calculate the full collaboration costs the set of requests is equal to all requests of all FFs. To calculate the individual planning costs for one FF the set of requests is set to only the requests from that specific FF.

In this paper the total amount of allowed run time is set for every SA performed. Normally the probability of accepting a worse neighbour solution as the new current solution depends on a temperature T that decreases with every iteration. In this paper the temperature T is equal to the amount of time that is left of the total allowed run time for the SA. The probability of accepting neighbour solution S^*, if $J(S^*) > J(S_c)$, is determined by the following probability function: $P(S^*) = exp\,[(\ J(S_c) - J(S^*))/(T)]$.

In each iteration of the SA framework a new neighbour solution is found with a Large Neighbourhood Search (LNS). The LNS generates a new solution $S*$ from the current solution S_c by randomly choosing a removel operator that removes requests from a route and then randomly choosing a insertion operator that inserts requests into a route. The removal operators are: 1. Shaw removal, (Shaw, 1997), (Ropke and Pisinger, 2004). 2. Random removal, (Ropke and Pisinger, 2004). 3. Worst removal, (Ropke and Pisinger, 2004). 4. Shortest route removal, (Li et al., 2015). 5. FF-GH removal, (Bombelli and Tavasszy, 2020).

The insertion operators are: 1. Basic greedy insertion, (Ropke and Pisinger, 2004). 2. Tabu greedy insertion, (Ropke and Pisinger, 2004). 3. 2-Regret insertion, (Ropke and Pisinger, 2004). 4. Route addition, (Bombelli and Tavasszy, 2020).

After a removal and insertion pair has produced a new neighbour solution S^*, a routine is carried out to identify and reduce dock capacity violations without increasing other violations. In fact, while in the computation of J the overall dock capacity violation of the new solution is considered, no preemptive action is explicitly taken to limit such violation. The routine consists of two stages: Time slack strategy and departure time adjustment strategy. If, for example, two trucks arrive at the same dock at the same time, the time slack strategy tries to resolve the dock capacity violation by making one of the trucks wait on the other truck. The truck with the most time slack in their route is the truck that has to wait. The time slack of a route is explained in more detail in (Bombelli and Tavasszy, 2020). If it is possible to resolve the dock capacity violation with the time slack strategy without causing other violations, the departure time adjustment strategy is applied. If this is not possible the solution is discarded. With the departure time adjustment strategy it is possible to prevent waiting times (caused by early arrival) by adjusting the departure times of the trucks. If, for example, a delayed truck has to wait for 5 minutes for another truck to unload, it would have been better if that delayed truck left the origin depot ($\mathcal{O}_d$) 5 minutes later. In that case the truck would not have to wait the extra 5 minutes. Whether delaying the departure of a truck is possible is also based on the time slack of a route.

In the individual planning, a FF is not aware of the planning of other FFs. Therefore, the time slack strategy and departure time adjustment strategy can not be used for the individual planning. However, in the individual planning trucks do have to queue, this is modelled using only the time slack strategy.

2.3 Quantifying transport efficiency

Comparing the KPIs of one collaboration type with another shows the difference in performance on many different aspects of efficiency. It is also interesting to not only compare the overall system performance, but also the performance per FF. In this paper, the following KPIs are used: (1) Profit: The profit made by a FF is equal to the revenue minus the costs for transporting the requests to the GHs. The revenue is assumed fixed per FF and the costs only depend on the total transportation time. Consequently, the difference in the total profit between the types of collaboration gives insight into the cost efficiency of the overall transportation planning. (2) Distance travelled: The distance travelled of a collaboration type is defined as the sum of the distances driven by the trucks. Obviously, it takes time to travel a certain distance, so the distance is implicitly incorporated in the costs. To give a complete overview the distance is presented as well, where the distance is an indicator of the environmental impact. (3) Load factor: There are two load factors: weight and space. A higher load factor means that the trucks are more full, which indicates a more efficient use of resources like trucks and drivers. Additionally, it is an indicator of the environmental impact. (4) Waiting time for a dock to become available: The total waiting time of all trucks in a collaboration type gives insight into the amount of congestion at the GHs. (5) Amount of trucks: A reduction in the amount of required trucks could eventually reduce the investment costs of the coalition or of an individual FF. (6) Amount of truck arrivals at GHs: A truck arrival is defined as a truck that docks at a GH. The total amount of truck arrivals at the GHs provides insight in the truck congestion at the GHs.

2.4 Collaboration disadvantages

Although collaboration has been identified as a key factor in reducing transportation costs and increasing efficiency in most supply chains, its implementation is still not fully developed. This is mainly due to several factors that are perceived by stakeholders as disadvantages. In this paper the following aspects, that could become disadvantages, of collaboration are tracked: (1) Profit allocation: When FFs work together and obtain an increased joint profit, this profit needs to be divided over all participating FFs. A profit reallocation is considered fair if (a) All FFs make at least the same amount of profit after the profit reallocation compared to the individual situation (individual rationality) (b) FFs get higher profit shares if they contribute more to the total collaboration gain (proportional to contribution). (2) Autonomy: When different FFs collaborate they agree on a set of rules for their collaboration, which restricts them in making individual decisions. How many decisions, how the decisions are made and in whose best interest they are made is tracked for all five auction phases. (3) Ease of use: To track the ease of use, the amount of extra actions needed from the FFs to ensure a well functioning auction based coopetition system is identified. (4) Information sharing: For each step in the auction, the amount, the type and with who the information is shared is tracked. (5) Market position: The market position of a FF is determined by its share of the transportation market relative to the shares of its competitors in the same market. A possible downside of collaboration is that competitors (FFs) could obtain information about each others pricing. With this information they could try to undercut their competitors, causing the others to lose market share.

3 Auction model

The overall auction model consists of five phases. Each of the five phases requires input from the previous phase or additional data. In Figure 5 a graphical overview of the five phases can be found.

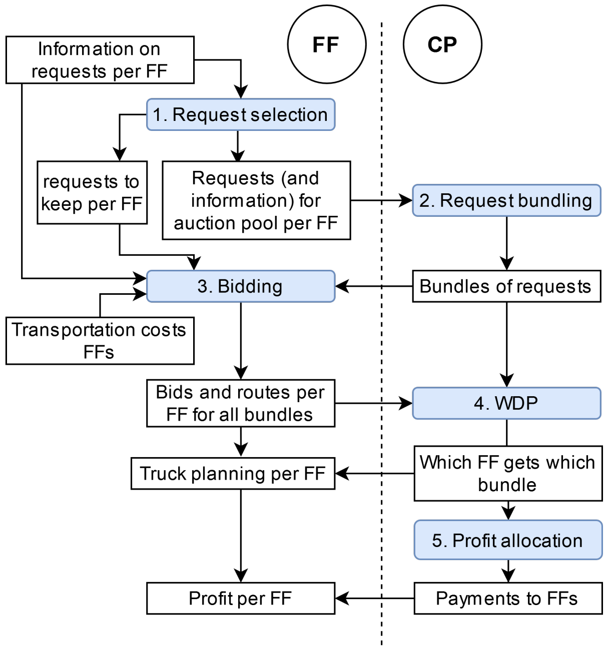

Figure 5: Overview of the auction model. Left: actions by the FFs. Right: actions by the central planner. Horizontal arrows represent information exchanges between the FFs and the central planner and vice versa.

3.1 Request selection

In this phase all FFs individually decide which requests they want to keep and which requests they want to submit to the auction pool. This decision is based on predetermined characteristics of the requests. No exchange of information is needed between FFs or to the central planner. The input for the request selection phase is information on all requests per FF. For each request r_i, consisting of pickup node i and delivery node $i + \sigma$, the location and the time window of the delivery is known to the FF. Studies have shown that selecting requests based on a characteristic that can make a request unattractive for one FF yet attractive for another is more effective, for the entire coalition, than only selecting on profit or revenue (Gansterer and Hartl, 2016), (Schopka and Kopfer, 2017). In the landside air cargo supply chain such a characteristic is the location of the delivery combined with the time window in which the request needs to be delivered at that GH. For example: a FF may have to deliver three requests at GH1 within similar time windows and two requests at GH2 at completely different time windows. The three requests with a similar delivery time window are more attractive for this FF to keep. Furthermore, there is a chance that the other two requests are attractive for other FFs of the consortium.

The similarity of two time windows is determined by the amount of overlap they have. The amount of overlap between node i and node j (o_{ij}) is calculated with $o_{ij} = \max(0, \min(l_i, l_j) - \max(e_i, e_j))$. The amount of overlap of a group of nodes ($o_{i,j,\cdots,m,n}$) is calculated with $o_{i,j,\cdots,m,n} = \max(0, \min(l_i, l_j, \cdots, l_m, l_n) - \max(e_i, e_j, \cdots, e_m, e_n))$.

For each FF the requests are sorted on delivery location. All delivery nodes with pick up at FF f and delivery at GH g are denoted by $\mathcal{B}^{\mathcal{G}}_{fg}$. The total overlap an individual delivery node (o_i) has with all other requests in $\mathcal{B}^{\mathcal{G}}_{fg}$, is calculated with $o_i = \sum_{j \in \mathcal{B}^{\mathcal{G}}_{fg}} o_{ij} \quad \forall i \neq j$. The total overlap of a set of delivery nodes (o_S) is calculated with $o_S = \sum_{i \in S} \sum_{j \in S} o_{ij} \quad \forall i < j$.

Example 3.1 *FF1 has to deliver the requests summarised in Table 1, with nodes* $13, 14, 15 \in \mathcal{B}^{\mathcal{G}}_{11}$ *and* $16, 17, 18 \in \mathcal{B}^{\mathcal{G}}_{12}$. *To clarify the notation: request 1 consists of pick-up node 1 and delivery node 13, which also shows that* $sigma = 12$.

Based on the overlap calculations the following selection criteria were considered: (1) For each FF, keep the requests that individually have the highest amount of total overlap (o_i). The requests with delivery nodes 13, 15, 17 and 18 in example 3.1. (2) For each FF, keep the requests that have the highest amount of overlap as a group ($o_{i,j,\cdots,m,n}$). The requests with delivery nodes 13,14 and 15 in example 3.1. (3) For each FF, keep the requests that have the highest amount of overlap as a set (o_S). The requests with delivery nodes 13,14 and 15 in example 3.1.

Table 1: Delivery data FF 1.

request	node	FF	GH	e_i	l_i	o_{ij}	o_i	$o_{\mathcal{B}^{\mathcal{G}}_{1j}}$
1	13	1	1	300	480	$o_{13,14} = 40$	220	
2	14	1	1	160	340	$o_{14,15} = 40$	80	260
3	15	1	1	300	480	$o_{15,13} = 180$	220	
4	16	1	2	300	480	$o_{16,17} = 0$	0	
5	17	1	2	100	280	$o_{17,18} = 180$	180	180
6	18	1	2	100	280	$o_{18,16} = 0$	180	

In this paper a combination of method (3) and (1) is chosen that ensures the requests are chosen as a set and outliers of the set are excluded. First, method 3 is applied to select the initial set of requests to keep. Then the total overlap of each individual request (o_i) in this set is evaluated against a preset minimum. If the request does not meet the preset minimum, it will be put into the auction pool. Selection of the best set continues until the threshold, a percentage that depicts the minimum amount of requests the FF wants to keep, is met. All requests that are not selected are put into the auction pool.

3.2 Request bundling

Once each FF has decided which requests to keep, each FF communicates to the central planner which requests are put into the auction pool. The set of requests in the auction pool is denoted by $\mathcal{A}$. FFs do not share information on their routing or their capacity constraints with the central planner in this phase. The central planner only needs to know the location and the time window of delivery of all requests in the auction pool. In phase four of the auction system each FF is assigned one or no bundle. Therefore, the number of bundles that are reassigned is always less or equal to the number of FFs (N_f). Because each request can only be assigned to one FF, the objective of the bundling phase could also be seen as finding promising partitions of the auction pool. The partitions consist of at most N_f bundles. The collection of bundles is denoted by $\mathcal{D}$, which is initially an empty set. Suggestions for bundle criteria for selecting promising bundles: (1) Requests in the same bundle have the same delivery location. (2) Requests in the same bundle have a high amount of overlap at a GH location. (3) A bundle in itself is only promising if the rest of $\mathcal{A}$ is partitioned into at most $N_f - 1$ promising bundles.

The following steps are executed to add promising bundles (not yet included in $\mathcal{D}$) to $\mathcal{D}$: (i) All requests in $\mathcal{A}$ are sorted by their delivery location: $\mathcal{A}_j^{\mathcal{G}}$ = requests in the auction pool with delivery at GH j. The first sets of requests that are added to $\mathcal{D}$ are $\mathcal{A}_j^{\mathcal{G}}\ \forall j \in \mathcal{G}$. These bundles form a partition of the auction nodes that comply with criteria (1) and (3). (Assuming there are more (or equal) FFs than GHs). (ii) All requests in $\mathcal{A}$ are sorted by their pickup location: $\mathcal{A}_i^{\mathcal{F}}$ = requests in the auction pool with pickup at FF i = the requests that FF i put into the auction pool. To ensure feasibility of phase 4, the sets of requests $\mathcal{A}_i^{\mathcal{F}}\ \forall i \in \mathcal{F}$ are added to $\mathcal{D}$. (iii) All requests in $\mathcal{A}$ are sorted by their pickup and delivery location: $\mathcal{A}_{ij}$ = requests in the auction pool with pickup at FF i and delivery at GH j. The $\mathcal{A}_{ij}$ comply with criteria (1) and are added to $\mathcal{D}$. (iv) The requests per GH in the auction pool ($\mathcal{A}_j^{\mathcal{G}}$) are partitioned into sets of requests that have a high amount of overlap with each other. This partitioning is done with hierarchical clustering, where the resulting clusters can be seen as bundles. The amount of overlap between any two requests in $\mathcal{A}_j^{\mathcal{G}}$ denotes the closeness of those requests. The distance between any two requests is the maximum overlap in $\mathcal{A}_j^{\mathcal{G}}$ minus the overlap between the two requests. The linkage criterion used is complete-linkage clustering. More about hierarchical clustering can be found in (Johnson, 1967). These type of bundles comply with criteria (1) and (2).

For the bundles produced with steps (i) to (iv), the main problem with complying to criterion (3) is that $\mathcal{A}$ is partitioned into too many bundles. Therefore, some bundles are combined to form new bundles, those are $\mathcal{A}_j^{\mathcal{G}}$. A combination of two bundles is simply a bundle that contains all requests from both bundles. This combination method limits the amount of extra bundles added to $\mathcal{D}$, namely $\binom{Ng}{2}$ bundles, where Ng is the number of GHs.

3.3 Bidding

It is imaginable that a FF does not want to handle certain types of requests. It is possible to incorporate this into the model by allowing the FF not to bid on that bundle. However, to ensure maximal flexibility of the solution, it is assumed that every FF bids on every offered bundle. Only if a FF is not capable of handling a certain bundle, they do not bid on that bundle. The bids in the combinatorial auction are based on the marginal profits of a FF for handling the requests in the bundles. The marginal profit of handling bundle b for FF f is defined as the profit with bundle b minus the profit without bundle b, the latter being the same as the profit of only handling the kept requests, see request selection phase in section 3.1. The profit of handling a set of requests is determined by the revenue a FF obtains from the shipper minus the costs of handling those requests. As mentioned before, FFs keep their initial revenue. However, the cost of serving the requests is not known yet. To determine the costs of handling a set of requests a routing problem must be solved. In this project the routing problems are solved with the meta heuristic discussed in Section 2.2. For each bundle, two routing problems must be solved:

1. FF f calculates the cost of handling bundle b ($cost_{with}^{fb}$) by solving the routing problem with the kept requests and the bundle requests.

2. FF f calculates the costs of only handling the requests that they kept ($cost^{f}_{kept}$) by solving the routing problem with only the kept requests.

The extra cost of handling bundle b for FF f is called the marginal cost: the cost of handling the kept requests with the requests in the bundle minus the cost of only handling the kept requests ($cost^{fb}_{with} - cost^{f}_{kept}$). The FFs communicate the marginal costs of all bundles to the central planner. Notice that the FF does not communicate the cost or profit of their initial route planning nor their initial revenue.

The central planner can then calculate the marginal profit of handling bundle b for FF f (mp_{fb}). Again it is important to note that revenue is not reallocated between the FFs nor is extra revenue created. Thus, the marginal revenue is zero. That means that the only way the auction coopetition can create extra profit for all FFs is to reduce the total transportation costs. The bid on bundle b from FF f is set as the marginal profit. The central planner constructs a bid matrix (MP) based on the marginal profits of the FFs, where $N_{\mathcal{B}} =$ number of bundles. The amount of routing problems that need to be solved is $N_{\mathcal{F}} * (N_{\mathcal{B}} + 1)$. This shows why it is important to keep the number of bundles limited.

$$MP = \begin{pmatrix} mp_{1,1} & mp_{1,2} & \cdots & mp_{1,N_{\mathcal{B}}} \\ mp_{2,1} & mp_{2,2} & & \vdots \\ \vdots & & \ddots & \\ mp_{N_{\mathcal{F}},1} & \cdots & & mp_{N_{\mathcal{F}},N_{\mathcal{B}}} \end{pmatrix}$$

3.4 Winner determination problem

The central planner calculates the optimal reallocation of the bundles based on the bids of the FFs. The required input for the winner determination problem (WDP) is shown in Table 2. The central planner is also informed about the number of docks the GHs have reserved for the participants of the collaboration: $N^{g}_{\mathcal{D}}$ = number of docks available at GH g, which is set to 1 in this project. The outcome of the WDP is a bundle to FF assignment that maximises the total system's marginal profit. For example, if bundle b is assigned to FF f this is denoted as $x_{fb} = 1$. To also take the dock capacity into account the central planner calculates all dock capacity violations between every bundle to FF assignment. In Table 2 all required information for this calculation is shown.

Parameter	Description
mp_{fb}	Bid from FF i on bundle b
rk_f	Routing of only kept requests by FF f
rw_{fb}	Routing of kept requests by FF f with bundle b
tk_f	Corresponding timestamps[a] of only kept requests by FF f
tw_{fb}	Corresponding timestamps[a] of kept requests by FF f with bundle b

[a] Timestamps are the departure and arrival times for each node in the route planning

Each bid is based on a truck routing with corresponding timestamps. Therefore, the central planner now knows at what time every truck arrives at a GH. If in assignment x_{fb} and x_{uv} two trucks arrive at the same GH at the same time, this is a dock capacity violation. The amount of dock capacity violations between assignment x_{fb} and x_{uv} is denoted with: $DC_{fb,uv}$. The mathematical model of the WDP is formulated based on the paper by Gansterer and Hartl (2016), see Table 3 and the mixed integer linear program (equations 1 to 8). The objective function (1) maximises the total marginal profit of the entire auction system. Each FF can win at most one bundle (2) and each bundle can only be assigned at most once (3). Constraint (4) ensures that each request is assigned exactly once. A FF can only win a bundle if he submitted a bid for the bundle (5). Constraint (6) regulates that if two bundle to FF assignments are chosen, that have a dock capacity violation, the decision variable k is set to the number of dock capacity violations. If only one of the two assignments is chosen, decision variable k remains zero. (7) defines that all x_{fb} are binary and (8) defines that $k_{fb,uv}$ is always a natural number. This mathematical formulation can be seen as an extension of the well known set partitioning problem. To guarantee feasibility, the central planner created feasible bundles as mentioned in

Section 3.2. The output of the WDP is a bundle to FF assignment, which means that each FF receives an overview of which requests they have to transport. The routing plan for these requests were calculated by themselves with the predetermined meta heuristic from Chapter 2.2.

Notation	Description
$\pi(MP, \mathcal{D})$	Total marginal profit after solving the WDP.
$\mathcal{D}$	Set of offered bundles, $b \in \mathcal{D}$.
MP	Matrix containing the bids.
mp_{fb}	Bid from FF f on bundle b.
C	Cost associated with a dock capacity violation in the WDP.
$\mathcal{F}$	Set of FF, $f \in \mathcal{F}$.
$\mathcal{R}$	Set of requests, $r \in \mathcal{R}$.
W_{br}	0/1 Parameter indicating whether request r is included in bundle b or not.
Q_{fb}	0/1 Parameter indicating whether FF f submitted a bid for bundle b or not.
$DC_{fb,uv}$	Parameter indicating the number of dock capacity violations between x_{fb} and x_{uv}.
x_{fb}	Decision variable indicating whether bundle b is assigned to FF f.
$k_{fb,uv}$	Decision variable indicating the number of dock capacity violations if there is a dock capacity violation in the bundle to FF assignment. Initially these are all set to 0.

$$\pi(MP, \mathcal{D}) = max \sum_f \sum_b mp_{fb} * x_{fb} - C * \sum_f \sum_b \sum_u \sum_v k_{fb,uv} \tag{1}$$

$$\sum_b x_{fb} \leq 1 \qquad \forall f \in \mathcal{F} \tag{2}$$

$$\sum_f x_{fb} \leq 1 \qquad \forall b \in \mathcal{D} \tag{3}$$

$$\sum_f \sum_b x_{fb} W_{br} = 1 \qquad \forall r \in \mathcal{R} \tag{4}$$

$$x_{fb} \leq Q_{fb} \qquad \forall f \in \mathcal{F},\ \forall b \in \mathcal{D} \tag{5}$$

$$(x_{fb} + x_{uv}) * DC_{fb,uv} - k_{fb,uv} \leq DC_{fb,uv} \qquad \forall f, u \in \mathcal{F},\ \forall b, v \in \mathcal{D} \tag{6}$$

$$x_{fb} \in \{0, 1\} \qquad \forall f \in \mathcal{F},\ \forall b \in \mathcal{D} \tag{7}$$

$$k_{fb,uv} \in \{0, 1, 2, \cdots\} \qquad \forall f, u \in \mathcal{F},\ \forall b, v \in \mathcal{D} \tag{8}$$

There are two possible outcomes of the WDP:

1. A bundle to FF assignment that has no dock capacity violations. In this situation, the route planning of each FF is feasible in combination with the route planning of all other FFs. Therefore, the planning can be executed accordingly.
2. A bundle to FF assignment with dock capacity violations. Here, the violations need to be solved. If there are dock capacity violations in the outcome of the WDP, decision variable k shows which bundle to FF assignments cause the dock capacity violations. If for example x_{11} and x_{22} need the same dock at the same time, the $k_{11,22}$ will denote the number of dock capacity violations between this pair. An algorithm finds the exact time and location of the dock capacity violation and tries to shift the timestamps of the arriving trucks in such a way that the routes become feasible. More about this procedure, called the time slack strategy and the departure time adjustment strategy, can be found in 2.2. If it is not possible with this procedure to solve the dock capacity violations in the routes, the WDP is called again to find an alternative bundle to FF assignment. This is done by adding an extra constraint to the WDP based on $k_{fb,uv}$. The extra constraint ensures that in the

new solution x_{11} and x_{22} can not both be chosen: If $k_{fb,uv} \geq 1$ the following constraint is added to the WDP: $x_{fb} + x_{uv} \leq 1$. This procedure is an iterative approach, as the new bundle to FF assignment may again contain an unsolvable dock capacity violation. If it is not possible to find a feasible bundle to FF assignment within an acceptable amount of iterations (15), the iterative algorithm is stopped and all FFs handle their original requests themselves (going back to complete individual planning).

In this project the dock capacity violations are solved in this phase, the WDP. There are other moments where the dock capacity can be solved. For instance, even before the request selection the delivery time windows of the requests could be adjusted in such a way that all requests get a mutually exclusive time window. So each request can be delivered in their own time window and no other request. Unfortunately, this restricts the entire solution space of the problem unreasonably. Another option would be to take the dock capacity into account in the request selection and bundling phase. The metaheuristic used for the bidding in this project does take into account the dock capacity, as is explained in Section 2.2. If all requests that go to the same GH are transported by the same FF, the metaheuristic ensures that there is no dock capacity violation at that GH. However, this would simply mean a redistribution of the requests where each FF is assigned all requests that go to one GH. This is no longer an auction coopetition as defined in this project.

3.5 Profit sharing

In this phase the extra profit obtained by the coopetition is distributed among the FFs. This phase is executed by the central planner and it does not require additional information. In this paper a new profit sharing mechanism, developed by Gansterer et al. (2019b), is chosen because of the following characteristics: (1) Profit reallocation is fair as described in 2.4. (2) Profit reallocation can be executed without critical information. (3) Profit reallocation ensures group rationality. (4) Profit reallocation is computationally manageable. All necessary information for the profit reallocation is derived from: (A) The bids on the bundles that the FFs are assigned in the WDP. φ_f is defined as the marginal profit for FF f of handling the assigned bundle, i.e. the marginal profit (negative marginal cost) of handling the acquired requests. (B) The bids of the FFs on bundles consisting of their own offered requests. ξ_f is defined as the marginal profit for FF f of the bundle that consists of the requests that were put into the auction pool by FF f, i.e. the marginal profit (negative marginal cost) of handling the FFs initially offered requests.

Subsequently, the central planner can now establish how much profit each FF will gain, if adhering to the request assignment found in the WDP. For each FF the amount of extra profit is equal to $\vartheta_f = \varphi_f - \xi_f$. This is equal to the gained profit by buying requests minus the missed profit for selling requests for FF f. The total extra profit gained by the auction based coopetition is $\Theta = \sum_{f \in \mathcal{F}} \vartheta_f$. This extra profit is distributed among the FFs in the coopetition with profit sharing equation: $\lambda_f = \frac{\Theta}{2}\left(\frac{|\varphi_f|}{\Phi} + \frac{|\xi_f|}{\Xi}\right)$, which assigns the weighted average of contributed sales and purchases to each FF. To ensure individual and group rationality, the sum of the absolute values of the marginal profits is used. The marginal profit for buying requests for the total coopetition is $\Phi = \sum_{f \in \mathcal{F}} |\varphi_f|$, the marginal profit for selling requests for the total coopetition is $\Xi = \sum_{f \in \mathcal{F}} |\xi_f|$. The amount FF f pays to the central planner is equal to $max(0, \vartheta_f)$. So only if serving the requests in the bundle costs less than serving their initially offered requests, the FF pays the central planner. The total share of the extra profit FF f obtains from the central planner consists of two parts: 1) compensation for extra costs and 2) a share of the total collaboration gain (λ_f). The compensation of a FF is equal to the extra costs made by following the WDP assignment: compensation$_f = -min(0, \vartheta_f)$. An example is shown in Table 4.

Table 4: Example of the profit sharing mechanism

FF	buys bundle	φ	ξ	ϑ	pay to CP	Compensation	λ = Extra Profit	Pay to FF
A	a	-4	-12	8	8	0	$\frac{10}{2} * \left(\frac{4}{16} + \frac{12}{26}\right) = 3.56$	3.56
B	b	-3	-8	5	5	0	$\frac{10}{2} * \left(\frac{3}{16} + \frac{8}{26}\right) = 2.48$	2.48
C	c	-9	-6	-3	0	3	$\frac{10}{2} * \left(\frac{9}{16} + \frac{6}{26}\right) = 3.97$	6.97
Total		16	26	10	13	3	10	13

4 Results

First, the three collaboration types are compared on the KPIs, as defined in Section 2.3. Second, the auction coopetition is analysed on possible collaboration disadvantages, which results in a trade-off, which is discussed in 4.2. To ensure a valid comparison between the different types of collaboration, the allowed run time for each collaboration type is set to an equal amount of time in a real world scenario (ART). If the ART is set to 60 minutes this means that: The full collaboration can run for 60 minutes. All FFs can run their individual planning for 60 minutes each ($N_{\mathcal{F}} * 60$ in total). The auction coopetition can run for almost $N_{\mathcal{F}} * 60$ minutes, as phase 3 (the most time consuming phase) is performed parallel at the different FFs.

4.1 Comparison on collaboration efficiency

As mentioned in Section 2.3, the three different collaboration types are compared on the following KPIs: 1. Profit (Pr). 2. Distance travelled (Di). 3. Load factor (LF_{we} and LF_{wi}). 4. Waiting time for a dock to become available (WT). 5. Amount of trucks (Tr). 6. Amount of truck arrivals at the GHs (TGH). The name of the instance indicates in order: the number of FFs, the number of GHs and the amount of requests in the data instance. The partition of the total amount of requests per FF is shown below the instance name. In Table 5 and Figure 6 the results for the 3_2_27 instance can be found.

Table 5: Results of instance 3_2_27

Instance	ART	Type	Pr	Di	LF_{we}	LF_{wi}	WT	Tr	TGH	Pr per FF
3_2_27	10	I	127	99	68	61	47	7	9	[78, 13, 35]
[9, 11, 7]		A	202	86	67	61	0	7	7	[87, 58, 58]
		F	187	95	93	85	0	5	8	-
	60	I	139	98	78	71	38	6	9	[79, 25, 35]
		A	203	87	67	61	0	7	7	[85, 60, 58]
		F	195	92	93	85	0	5	8	-

As one can see in Table 5, the auction coopetition performs best on profit, distance, waiting time and the amount of trucks arriving at the GHs. The load factors of the auction coopetition and individual planning are almost the same, while the full collaboration has much higher load factors. The load factors directly correspond to the number of trucks. For the auction coopetition, the profit increase compared to the individual planning for FF2 stands out. All three collaboration types do improve, yet not significantly, when the ART is increased from 10 to 60 minutes. For both the auction coopetition and the full collaboration the waiting time is zero, while this is not the case for the individual planning. Here the effect of a central planner can clearly be seen.

The profit of the auction coopetition is 46% higher than the individual planning, while using more trucks. Another main difference can be found in the routing of the trucks. In the individual planning each FF has to visit both GH1 and GH2, which causes three truck movements between the two GHs. In the auction coopetition, requests get reassigned to FFs in such a way that there are no movements between the two GHs. In the auction coopetition the central planner has information on which truck needs to be at a GH at which time, this information is shared in the bidding phase. Therefore, the central planner can decide to delay a truck at the origin depot, such that there are no two trucks arriving at one GH at the same time.

In the full collaboration the amount of trucks is the lowest. It is interesting to see that there are a three truck movements between the GHs and four between the FFs. Apparently, the low amount of required trucks is compensated by more truck movements on both sides of the truck planning. Additionally, the full collaboration of the 3_2_27 instance is run with an exact solution method. The incumbent solution found after a six hour run was a total profit of 219. This solution is roughly 8% better than the solution found with the auction coopetition model.

In Table 6 the results for the 4_3_50 instance are shown for the ART of 10 and 60 minutes. The auction coopetition performs best on profit, distance, waiting time and truck arrivals at the GHs. Remarkably, in the full collaboration the amount of used trucks goes up when increasing the ART from 10 to 60 minutes, even though the profit increases. Similarly, in the auction coopetition the amount of truck arrivals at the GHs goes up, while the profit increases. These changes could be caused by the fact that the cost of the routing only depends on the total travel time and not on the truck use.

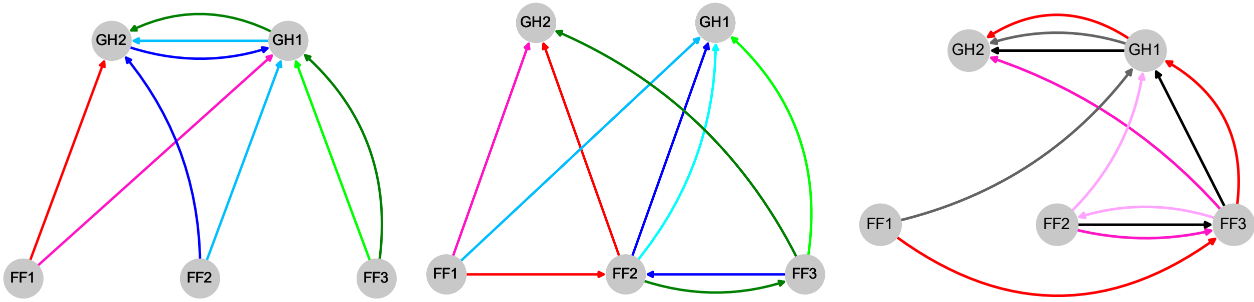

Figure 6: 3_2_27, ART = 60. Routing of the trucks: **I** (L), **A** (M), **F** (R). In **I** and **A**: tints of red = FF1, tints of blue = FF2, tints of green = FF3.

Table 6: Results for instance 4_3_50

Instance	ART	Type	Pr	Di	LF_{we}	LF_{wi}	WT	Tr	TGH	Pr per FF
4_3_50 [12,10,14,14]	10	I	205	142	81	74	172	11	23	[-14, 57, 89, 74]
		A	406	127	74	67	0	12	12	[83, 91, 115, 116]
		F	235	183	87	80	33	10	21	-
	60	I	214	142	81	74	164	11	23	[-15, 43, 81, 106]
		A	424	117	72	66	0	12	14	[99, 90, 117, 117]
		F	246	184	58	53	16	15	24	-

4.2 Trade-off with collaboration disadvantages

In the auction coopetition the redistribution of the extra profit is done in such a way that every FF is compensated for their possible losses. Hence, individual rationality is guaranteed. The share of the extra profit that is obtained by every FF is determined by their contribution (by buying or selling requests) to the coopetition. Consequently, the profit sharing mechanism defined in this paper is considered fair, as defined in Section 2.4. The FFs do lose most of their autonomy over the requests they put into the auction pool. Most decisions, of the CP, are made in the best interest of the entire coalition. Overall, most extra actions, required for a fully functioning auction coopetition, concern data exchanges or relatively simple parameter specifications. Therefore, the auction coopetition is relatively easy to use for the FFs. It is important to notice that in the auction based coopetition a FF is never required to share: 1. Their initial price to the shipper for handling a request (revenue per request). 2. Their initial profit. 3. Their initial amount of requests. 4. Their profit of the bundles. 5. Their cost structure. Because the auction coopetition prevents the exchange of critical company information, there is no chance of losing your market position due to the exchange of information. However, it could be possible that implicit information can be retrieved from the redistribution of the requests. Further investigation of this phenomenon is required.

The auction coopetition seems to perform the best on several of the transport efficiency KPIs. Especially on the KPIs that are used as indicators for the amount of truck congestion at the GHs, waiting time and the amount of truck arrivals at the GHs. The full collaboration also performs very well on the waiting time KPI. In the individual planning the waiting times are always the highest, which makes sense, because there is no central planner to avoid queuing. The waiting time increases the costs for the FFs considerably. Because, in the individual planning, the FFs do not know the planning of the other FFs, it is possible that for one FF the waiting time is so high its profit becomes negative. On forehand, there is no way for the FFs to know if this will occur, which causes uncertainty in their planning and their profit.

Both the decrease in congestion and the increase in certainty are clear indicators of the added value of a central planner. Both in the auction coopetition and the full collaboration, the amount of total travel time, which waiting time is a part of, for all FFs is minimised. If there is still waiting time remaining in the planning, the associated cost are fairly divided over all collaborating FFs. This increases the certainty for the FFs and their profitability. Therefore, the profit reallocation mechanism is considered an advantage rather than a disadvantage.

The auction coopetition consistently performs the best in terms of profit. The total profit of the auction coopetition is the highest in every data instance run in Section 4.1. Additionally, the profit per FF seems to be divided more evenly across the FFs compared to the individual planning. Furthermore, the auction coopetition performs quite well in a short ART (10 minutes), where the full collaboration probably needs a lot more computational time to find an equally good solution. There are some downsides to the auction coopetition. In many of the instances from Section 2.3, the auction coopetition requires the most amount of trucks. This causes the load factors to somewhat decrease, which is a KPI of the environmental impact. On the other hand, the auction coopetition does frequently perform the best on the distance KPI, which is also an environmental impact indicator.

5 Discussion and Conclusion

The main contribution of this paper is twofold. First, the fully integrated five phase auction based coopetition model is a methodological contribution. A unique aspect is the fact that the dock capacity of the ground handlers is taken into account in an auction based model. Also, the developed request selection and bundling procedures are based on the time windows of the request deliveries. Second, the potential of such an auction based coopetition is shown for an air cargo supply chain scenario. There is a clear increase in profitability for the freight forwarders and a decrease in congestion at the ground handlers. Furthermore, the total travelled distance decreases, which indicates a beneficial environmental effect. The disadvantages of the auction based coopetition are limited due to the auction phases used in this paper. The data used in this paper is artificial. Therefore, it would require more research to establish the real world potential of the auction based coopetition system presented in this paper.

The solution space of the auction coopetition is reduced in the earlier phases, which probably causes the KPIs to only slightly improve by increasing the ART. Because the solution space is smaller, the optimal solution is worse than (or equal to) the optimal solution of the entire (full collaboration) problem, but is found faster. Therefore, it seems likely that the auction coopetition model is able to find a decent solution within restricted computational time.

Network flexibility is seen as the amount of options a FF has to fulfil all transportation requests. With an increase in, for example, the amount of initial requests (size of a FF), the amount of transportation options increases. Network flexibility becomes an issue when a FF can retrieve implicit information about the pricing of another FF, by always winning their requests. The possibility to retrieve implicit information should be investigated further.

The difference in the results of the individual planning and the auction coopetition are larger than in literature. This could be caused by the following factors: (1) The dock capacity of the GHs is taken into account, which is a unique feature of this paper. This causes a part of the differences (in profit) between the individual planning and auction coopetition. In larger instances this difference further increases because more dock capacity violations occur in the individual planning. (2) The simulated annealing approach chosen in this paper seems to perform the best for the auction coopetition. (3) The solution space of the auction coopetition is much smaller than for the individual planning and the full collaboration. Therefore, the individual planning and full collaboration would require more time to find an equally good solution as the auction coopetition.

The auction based coopetition framework performed much better in less time than the full collaboration model. A future research direction would be to investigate which aspects of the auction model could also be used in a metaheuristic to speed up the search in the full collaboration model and the individual planning.

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B
Verification results

Table B.1: Verification phase 1

Parameter	Description	Default	Variation	Expectation	Check
k_i	Keep threshold FF i	1/2	0	All requests are put into the auction pool	✓
			1	$\mathcal{A} = \emptyset$	✓
			3/4	More requests are put into the auction pool than with the default	✓
overlap minimum	A preset minimum for the total overlap of a request	60 min	0 min	From the chosen set of requests, no individual requests are put into the auction pool	✓
			1000 min	All requests are put into the auction pool	✓

Table B.2: Verification phase 2

Parameter	Description	Default	Variation	Expectation	Check
k_i	Keep threshold FF i	1/2	0	More bundles than at default setting	✓
			1	No bundles are created	✓
			3/4	Equal or less bundles than at default setting	✓

Table B.3: Verification phase 3

Parameter	Description	Default	Variation	Expectation	Check
c_τ	cost per time unit	1.022	0	Total costs of the routes are 0	✓
			1000	Total costs of the routes increase significantly	✓
t_{ij}	Time it takes to go from node i to node j ($i \neq j$)	$2.36 \leq t_{ij} \leq 18.1$ min	0	Total costs of the routes is equal to only costs per time unit times the processing times	✓
			$*10$	Total costs of the routes increase significantly	✓
d_{ij}	Distance between node i and node j	$0.21 \leq d_{ij} \leq 9.4$ km	0	Total costs of the routes are unchanged	✓
			$*10$	Total costs of the routes are unchanged	✓
p_i	Processing time of node i	$2 \leq p_i \leq 10$ min	0	Total costs of the routes are reduced with the cost per time unit times the processing times	✓
			$*10$	Total costs of the routes are increased significantly	✓
rev_i	Revenue of node i	$20 \leq rev_i \leq 30$ monetary units	$*0$	Total costs of the routes are unchanged	✓
			$*100$	Total costs of the routes are unchanged	✓
Q	Weight capacity truck	$10,000$ kg	$20,000$	Total costs of the routes are less or equal to the default	✓
			0	Not able to build routes	✓
L	Lateral capacity truck	13.4m	20	Total costs of the routes are less or equal to the default	✓
			0	Not able to build routes	✓

Table B.4: Verification phases 1 to 5 part 1

Parameter	Description	Default[d][a]	Variation	Expectation	Profit per FF	Total profit	Check
k_i	Keep threshold FF i	$k_i = 1/2$	$k_i = 0$	Profit increases due to a less constrained feasible solution space [b]	[82, 25, 46]	154	✓
			$k_i = 1$	No exchange of requests, no auction			✓
			$k = [1, 1/2, 1/2]$	FF1 keeps all requests and does not participate by selling. This leads to a lower profit for FF1. [c]	[95, 48, 2]	145	✗[c]

[a] A FF can end up with a negative profit after the auction model if in the individual situation the FF had an even more negative profit.

, [b] Wrong expectation. The feasible solution space is determined in phase two (bundling), if the bundling of less requests is done more promising than the bundling of more requests, then the profit could decrease in a situation where the FFs have a lower threshold.

[c] Wrong expectation. FF1 can still participate by buying requests.

[d] Default values: Profit per FF = [59, -16, 68] and Total profit = 112.

Table B.5: Verification phases 1 to 5 part 2

Parameter	Description	Default[c a]	Variation	Expectation	Profit per FF	Total profit	Check
c_τ	cost per minute	1.022	0	There are no costs, so profit equals revenue.	[254, 117, 223]	594	✓
			$*10^b$	Costs increase, so profit decreases.	[-573, -1284, -1735]	-3592	✓
t_{ij}	Time it takes to go from node i to node j ($i \neq j$)	$2.36 \leq t_{ij} \leq 18.1$ minutes	0	Profit increases because costs are only based on processing times	[99, 58, 152]	309	✓
			$*2^b$	Profit decreases because it takes longer to deliver al requests	[59, -102, -63]	-106	✓
d_{ij}	Distance between node i and node j	$0.21 \leq d_{ij} \leq 9.4$ km	0	Profit is unchanged	[59, -16[a], 68]	112	✓
			$*2^b$	Profit is unchanged	[59, -16[a], 68]	112	✓
p_i	Processing time of node i	$2 \leq p_i \leq 10$ minutes	0	Profit increases because it takes less long to deliver al requests	[181, 71, 151]	403	✓
			$*2^b$	Profit decreases because it takes longer to deliver al requests	[-9, -121, -46]	-176	✓
rev_i	Revenue of node i	$20 \leq rev_i \leq 30$ monetary units	$*0$	Profit decreases and is equal to -costs	[-188, -100, -194]	-482	✓
			$*10$	Profit increases	[2347, 1030, 2081]	5458	✓
Q	Weight capacity truck	10,000 kg	20,000	Profits are higher or equal to the default	[59, -16[a], 68]	112	✓
			0	Not able to build routes			✓
L	Lateral capacity truck	13.4 m	20	Profits are higher or equal to the default	[59, -16[a], 68]	112	✓
			0	Not able to build routes			✓

[a] A FF can end up with a negative profit after the auction model if in the individual situation the FF had an even more negative profit.
[b] If a very big multiplier is chosen the solution becomes infeasible.
[c] Default values: Profit per FF = [59, -16, 68] and Total profit = 112.

C
Data

The generated data sets can be found at the following DOI:
http://dx.doi.org/10.4121/uuid:a2242d5d-a7bd-4978-85bf-9079f9bafeff

1. The number of requests between each FF-GH pair is randomly set between 2 and 7.
2. The distances between depots, FFs and GHs were computed with google maps. The distance matrix can be found in Appendix **??**.
3. The average speed of each truck is set to 35 km/h. Because, distances are relatively short and the roads used are local low speed roads.
4. The docking time of a truck (the amount of time it takes to reverse into a dock) is set to 2 minutes.
5. The requests are assumed to already be consolidated at the FF or somewhere upstream in the supply chain. In this project a request is either a container or a pallet with equal probability.
6. Pallet: weight normal distribution with standard deviation = 400, mean 2800, max 4600
7. Pallet: width = 3.18 m
8. Pallet: processing time triangular distribution mode = 7, min = 4, max = 10.
9. Container: weight normal distribution with standard deviation = 200, mean 1000, max 1500
10. Container: width = 1.54 m
11. Container: processing time triangular distribution mode = 4, min = 2, max = 7.
12. Half of the requests gets an early pick up time later than T=0. This time is randomly chosen between T=50 and T=120.
13. Each request gets a delivery time window of three hours. If the delivery can take place at the end of the planning horizon the time window becomes: $[300, 480]$
14. Half of the requests gets a delivery time window earlier than the end of the day. Assuming that multiple requests at a GH have to be loaded into the same aircraft, it makes sense that those requests have the same time window for delivery. Therefore, the delivery time window depends on which GH the request has to be delivered. Each GH has a set of possible delivery time windows. For example: GH 1 has to load 12 requests different aircraft. Half of these requests are allowed to arrive at the end of the planning horizon because the aircraft leave after T=480. The other half of these 12(=6) requests get an earlier time window than $[300, 480]$. Assume that there are 3 different aircraft leaving during the day, so three different possible time windows for these requests. For instance: $[50, 230]$, $[130, 310]$, $[210, 390]$. the 6 requests get a time window chosen randomly.
15. The transportation cost per minute (c_τ) is based on a paper by the American Transportation Research Institute (2018). They found a time cost of 66.65 dollars per hour, which translates to approximately 1.02 euros per minute.

	Depot	FF1	FF2	FF3	FF4	FF5	GH1	GH2	GH3	GH4	GH5	Depot
Depot	0	0.75	3	0.21	4.8	2.4	5.5	4.9	0.6	1.1	1.1	0
FF1	0.75	0	3.5	1	4.6	1.8	6.5	5.5	0.45	0.35	0.6	0.75
FF2	3	3.5	0	2.7	5	2.6	6.6	5.6	0.5	0.4	0.3	3
FF3	0.21	1	2.7	0	3.8	2.2	5.7	4.7	0.7	0.95	1.2	0.21
FF4	4.8	4.6	5	3.8	0	2.4	9.4	8.5	5.2	5.5	5.8	4.8
FF5	2.4	1.8	2.6	2.2	2.4	0	6.6	5.7	2.6	1.7	1.8	2.4
GH1	5.5	6.5	6.6	5.7	9.4	6.6	0	2.2	7	6.7	6.8	5.5
GH2	4.9	5.5	5.6	4.7	8.5	5.7	2.2	0	5.1	5.4	5.7	4.9
GH3	0.6	0.45	0.5	0.7	5.2	2.6	7	5.1	0	0.25	0.6	0.6
GH4	1.1	0.35	0.4	0.95	5.5	1.7	6.7	5.4	0.25	0	0.35	1.1
GH5	1.1	0.6	0.3	1.2	5.8	1.8	6.8	5.7	0.6	0.35	0	1.1
Depot	0	0.75	3	0.21	4.8	2.4	5.5	4.9	0.6	1.1	1.1	0

Table C.1: Distance matrix in km

D
Python code

All Python code used for this project can be found at the following DOI:
http://dx.doi.org/10.4121/uuid:926e372a-0a61-4654-99a1-50f5da960ea7