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Centralized Planning for Collaborative Service Network Design

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Abstract

Collaborative service network design aims to show potential cost savings through the cooperation of companies. The goal is to minimize total costs by selecting a suitable combination of transportation services to meet the demand. A single, fully informed central authority makes all of the decisions. While the concept of collaboration has been explored in similar problems, such as vehicle routing, this work presents a novel approach to service network design. A mathematical model is developed that enables the joint transportation of commodities from different companies. Solutions are compared with the non-collaborative approach, aiming to reflect the potential cost savings. Depending on the parameter characteristics of individual test instances, the results show an improvement of up to 22.5%. This demonstrates that the collaboration of companies can be highly advantageous.

Abstract

Collaborative Service Network Design versucht die mögliche Kostenersparnis darzustellen, welche durch die Kollaboration von Unternehmen erzielt werden kann. Durch eine passende Kombination von Transportverbindungen sollen die Nachfrage gedeckt und die Kosten minimiert werden. Die dafür notwendigen Entscheidungen werden von einer zentralen Autorität getroffen, die über vollständige Informationen verfügt. Während das Konzept von Kollaboration in ähnlichen Problemen wie Vehicle Routing (Tourenplanung) bereits erforscht wurde, liefert diese Arbeit einen neuen Ansatz im Service Network Design. Ein mathematisches Modell wird entwickelt, das es verschiedenen Unternehmen ermöglicht, Waren gemeinsam zu transportieren. Die Ergebnisse werden mit dem nicht-kollaborativen Ansatz verglichen, um die möglichen Kostenersparnisse darzustellen. Je nach Parametereigenschaften der einzelnen Testinstanzen kann eine Verbesserung von bis zu 22.5% erzielt werden. Dies zeigt, dass die Kollaboration zwischen Unternehmen von großem Nutzen sein kann.

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1 Introduction

Service network design (SND) is a tactical planning problem with the goal of satisfying a certain demand for commodities that need to be transported. In contrast to the vehicle routing problem (VRP), goods are not delivered to many different customers but to a rather small number of terminals. While customers in VRP are different for each problem, terminal positions in SND usually stay the same for a longer time period. SND can be seen as the problem one level before vehicle routing. Terminals are used for loading and possible transport connections. For every good, the origin, destination, and amount (multi-commodity flow) are given. Each service has a given capacity, while costs are related to transportation time and/or distance. Costs for trucks or other transportation services being used also need to be considered. The goal is to minimize the overall costs while selecting some combination of services to satisfy the demand. This problem is traditionally solved by one company on its own but could be done for multiple companies by one central consortium to gain efficiency in the design of a service network and consequently save costs.

Collaborative planning is not done yet in SND, bout could be done in two different ways. While collaborators cooperate individually in decentralized settings, in centralized planning, there is only one authority that has full information and takes the decisions for all companies. For this thesis, the latter case is used, as this approach can be solved in integrated models and the potential of collaboration can be better analyzed. One should mention that the overall savings through collaboration are automatically higher in centralized than in decentralized settings. Instead of auction-based decisions for service assignments in decentralized planning, the overall best solution is chosen without taking care of one specific company. In centralized planning, the distribution of profit is decided afterwards. This ensures that each participating company has at least the same costs as before the collaboration. Costs can be saved if companies work together to achieve a more efficient design of the service network with a smaller need for trucks. Terminals can be used for reloading between the single companies, considering only a small or, in the best case, no detour. A detour is only done if it is beneficial. This means that total truck requirements can be saved due to new reloading possibilities. The potential cost improvement of collaborative service network design compared to isolated planning is analyzed by creating two corresponding models that are tested on a variety of instances with different parameter settings. It can be assumed that the collaborative model yields a significant cost improvement.

A major part of the work is covered by the centralized planning model for collaborative service network design and its results, but a broader explanation of the literature around this topic is also required. Therefore, chapter 2 gives a literature review on related problems, where the impact of collaboration has already been tested, and an introduction to service network design in general. Chapter 3 focuses on the problem description and the mathematical model of collaborative service network design. In chapter 4, the computational study is presented, evaluating the potential of collaborative service network design under different parameter settings like varying numbers of commodities or companies or different cost ratios. The solutions that are influenced by the dedicated parameters are analyzed to gain managerial insights. Using Mosel Xpress, each instance is solved with the goal of reaching an optimal solution for the corresponding instance. Chapter 5 concludes the thesis by summarizing the most important results.

2 Related Literature

An overview of the existing literature on the subjects of collaborative planning **(2.1)** and service network design **(2.2)** is provided in this chapter. The references consulted provide a crucial framework for the remaining sections of this work.

2.1 Collaborative Planning

2.1.1 Introduction to Collaborative Planning

Companies are driven to find ways to boost efficiency due to a number of variables, including economic volatility, higher expectations of service, and competition. This can be achieved through collaboration with other competitors, where cost savings can be reached that would not be possible individually. Collaboration can be defined as a strong relationship between multiple companies with the goal of achieving cost reductions that are beneficial for all collaborating members.(Nadarajah and Bookbinder, 2013)

While collaborative planning has not been considered yet for service network design, the potential savings of collaboration have been investigated in some related problems.

Gansterer and Hartl (2017) give an overview of what has been done already considering collaborative vehicle routing. Although this field has been extensively researched, they mention that collaborative gain assessment in more complex systems, like multiple depots, has yet to be investigated. Moreover, it is discussed whether collaboration should be centralized or decentralized. In centralized settings, there is one authority, for example, an online platform, making all decisions. Due to the collaboration of the companies, this central authority has full information and therefore faces a standard optimization problem. Decentralized planning means that decisions are made together. Collaboration is done by cooperating but not giving away full information. In decentralized problems, the cooperating companies are usually not of equal ranking. It is well known that centralized planning yields higher total profits than a decentralized setting. Sharing profits gained is another important issue, which is covered at a later point in this work. The paper of Gansterer and Hartl (2017) includes many more useful papers that are related to collaborative planning.

Dai and Chen (2009), for example, have formulated a model for collaborative planning for the vehicle routing problem in less-than-truckload (LTL) transportation. A suitable example for LTL transportation would be parcel delivery. As customer demands should be fulfilled quickly, there is a need for frequent deliveries. LTL requires a lot of customer visits because it transports a wide variety of small-volume goods. For this problem, multiple carriers and/or shippers are considered within a transportation network. In the non-collaborative approach, each shipper has its own carrier, which needs to execute the delivery tasks on its own. Collaboration enables all shippers and carriers to put their delivery tasks and vehicle capacities together. The goal is to find the overall best set of vehicle tours that ends up with minimum total costs and satisfies all delivery quantities.

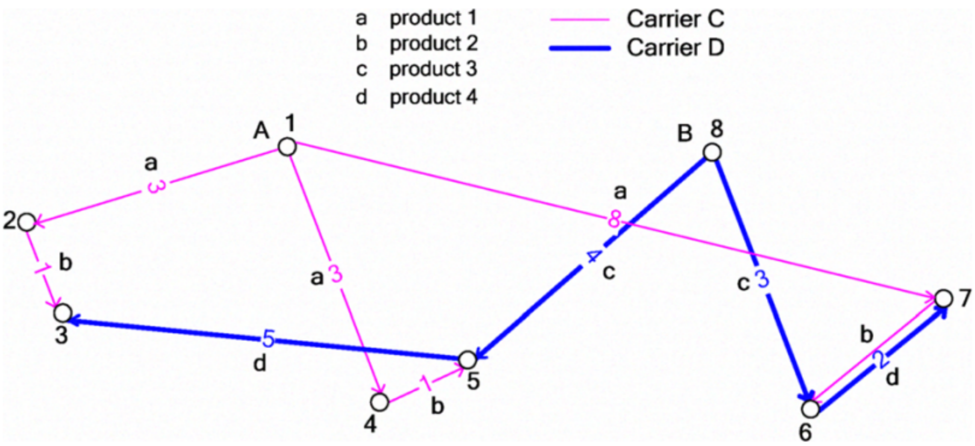

Figure 1: Transportation network
Dai and Chen (2009)

Figure1 shows an example of a small transportation network with two shippers (A and B) and two carriers (C and D). The pink lines represent the routes of carrier C, which is transporting products a and b before the collaboration. The blue lines represent the routes of carrier D, which is initially transporting products c and d. A and B mark the depots. The transportation distances are given for each arc and are equal to the transportation costs. This is a common procedure for problems involving transportation networks. Another simplification that was made is that each vehicle has the same capacity. Pickup and delivery can be done during the same tour to satisfy the delivery quantities of multiple customers. As this is a rather small problem, it is easy to find the optimal solution. This was done with the help of Cplex and led to the following solutions: Without collaboration for each carrier, the minimal costs are 22.5 (C) and 25 (D), which makes a total of 47.5. Note that in this case, shipper A is only served by carrier C, and shipper B is only served by carrier D. If the carriers collaborate, solving the problem with LTL transportation gives total costs of 29.5. This means that for this simple problem, 18 cost units have been saved through collaboration. (Dai and Chen, 2009)

2.1.2 A Collaborative Model for Less Than Truckload Transportation

After giving an idea about the potential of collaboration, the model of Dai and Chen (2009) for the collaborative logistics problem for less than truckload transportation will give a deeper understanding of this topic. All parameters, variables, and constraints are described below. The model is suitable for shipper and carrier collaboration and can be described as:

(A1) $Z = Min \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} c_{ij} * x_{ij}$

subject to:

(A2) $\sum_{j=1,j\neq i}^{N} x_{ij} = \sum_{j=1,j\neq i}^{N} x_{ji}$, i=1,...,N

(A3) $\sum_{k=1}^{K} q_{ij}^{k} \leq C * x_{ij}$, i,j=1,...,N

(A4) $\sum_{j=1,j\neq i}^{N} q_{ij}^{k} - \sum_{j=1,j\neq i}^{N} q_{ji}^{k} = \sum_{j=1,j\neq i}^{N} u_{ij}^{k} - \sum_{j=1,j\neq i}^{N} u_{ji}^{k}$, k=1,...,K and i=1,..,N

(A5) $x_{ij} \geq 0$, $x_{ij} \in Z$, i,j = 1,...,N $j \neq i$

(A6) $q_{ij}^{k} \geq 0$, $q_{ij}^{k} \in R$, k=1,...,K and i,j = 1,...,N $j \neq i$

Parameters used:
C: vehicle capacity
c_{ij}: transportation cost from node i to j (note that $c_{ij} = c_{ji}$)
u_{ij}^{k}: quantity k that is delivered form node i to j

Decision variables used:
x_{ij}: how often is arc i to j used by a vehicle
q_{ij}^{k}: quantity k that is transported through arc i,j

Objective function and constraints:
The objective function (A1) aims at minimizing the total transportation costs. Constraint (A2) ensures that the number of vehicles leaving a node equals the number of vehicles entering the node. In constraint (A3), the transportation amount of each vehicle is restricted to its capacity. If the capacity of a truck is exceeded, an additional truck must be employed. Constraint (A4) is the product flow conservation equation. These assure the correct flow balance of each product at each node. The last two constraint types (A5) and (A6) are used for the correct values of the decision variables. The number of vehicles must be positive and integer (A5), and the transported quantity has to be positive (A6).

An online platform was used as a central authority to make the planning decisions. Assuming that vehicles can exchange parts of their freight on every node they are visiting together, this gives the possibility of saving costs in comparison to the non-collaborative approach. It should be mentioned that costs for reloading have not been considered. For networks with large distances, the costs of reloading should not have a too big influence on the total costs, but it still needs to be remembered that some of the profit gained is needed for the costs of reloading. The flow balance constraint and the vehicle capacity constraint limit the reloading possibilities. (Dai and Chen, 2009)

2.1.3 Further collaborative planning approaches

The work of Nadarajah and Bookbinder (2013) would be another useful source. In their paper, they wrote about the less-than-truckload (LTL) carrier and collaboration problem. Less-than-truckload problems usually arise in more local regions and are suitable for collaboration, as exchanging single parts of the freight can be easily done and helpful for reducing transportation time. Moreover, in a more local setting, it often happens that the transportation routes of different carriers overlap. According to Nadarajah and Bookbinder (2013), the LTL carrier collaboration problem can be split into three sub-problems. The first sub-problem covers exchanging loads on so-called "entry points" in a city, considering the possible time windows and capacities of each vehicle. Allocating the potential positions of those entry points is the second sub-problem. Out of those potential positions, the third sub-problem aims at choosing the best of these positions, considering when the exchange should happen and which goods should be moved. Additionally, two restrictions, R1 and R2, have to be considered, which can be described as follows: Let's say a good should be transferred from vehicle V1 to vehicle V2. If V2 arrives first at the exchange point, it can wait a predefined maximum of t^w minutes for a feasible transfer of the goods from one vehicle to another vehicle (R1). In the other case (R2), if V1 arrives first, it would be efficient to temporarily store the goods in a certain area at the exchange point, from where they can be picked up by V2. The storage time of each good should not exceed a certain time t^s, to avoid congestion at the location.

Collaboration on the entry points to a city helped to reduce transportation distances by 7-15% and increase the utilization of vehicles by 3-4%. Given that trucks often travel empty, this is a significant side effect. Naturally, the goal is to minimize empty travel time in order to increase productivity and cut down on additional needless expenses.

Another example of collaborative planning can be seen in the paper of Cruijssen et al. (2007). They analyzed the results of collaborative vehicle routing with only one single distribution center. Companies want to cut back on so-called "non-value-adding tasks" such as distribution. This becomes even more important due to rising customer expectations and fierce market competition, to name two examples of tight profit margins. A possible way of saving distribution costs is outsourcing. This means that the logistics are done by a service provider outside the company, which is able to achieve economies of scale by serving multiple customers.

Cruijssen et al. (2007) give a practice example of joint route planning with three different catering companies operating all over the Netherlands. While the companies in this case study each have separate items to sell, there is an average 68% consumer overlap because schools, hospitals, and other institutions make up the majority of their clientele. Instead of three different distribution centers in the traditional setting, there is one central distribution center in Utrecht. Being in the center of the Netherlands made this location ideal from a strategic standpoint. All products were brought to the central distribution center, and logistics were outsourced and handled by one single service provider. Shipping the products from Utrecht brought a synergy value of 30.8%. This value can be defined as the difference between the total transportation distance of the initial approach and the joint route planning. Moreover, a fleet reduction of 50% has been achieved. Saving not only distance but also vehicles is a very important factor in reducing overall costs, as the costs of single vehicles can be very high. The actual change in transportation routes between joint route planning and the additional approach can be seen in figure 2. Comparing the left and right pictures, it is obvious that joint route planning leads to significant efficiency and cost improvements.

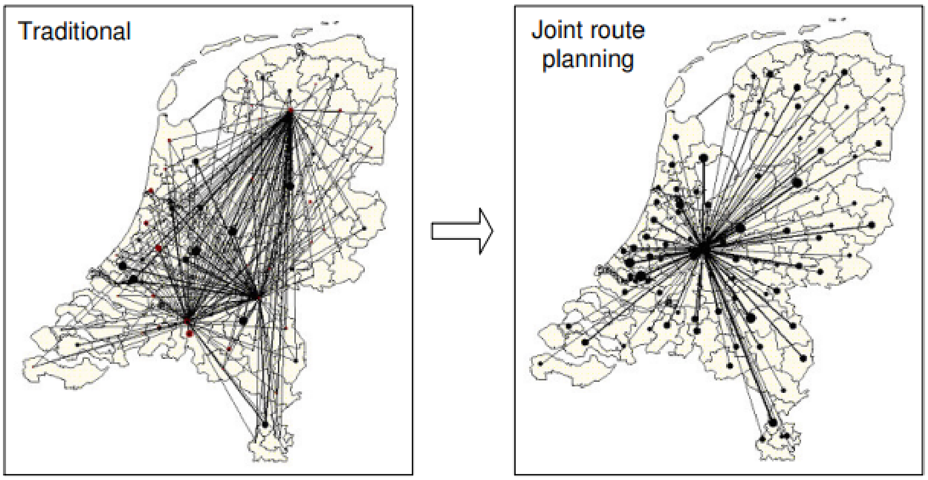

Figure 2: Potential of joint route planning
Cruijssen et al. (2007)

The previous example with a high customer overlap was very suitable for collaboration. This is not the case for every real-world problem, as the synergy value due to collaboration is very problem-dependent. Nevertheless, it is very important for companies to know the potential savings before forming partnerships. Therefore, an analysis was done on several factors that could influence the potential cost savings through collaboration. The influence of the number of orders per company, or, as it is called in the paper, per flow controlling entity (FCE), can be seen in figure 3. Tested for different numbers of FCEs, it can be seen that for a relatively small number of orders, the achieved cost savings are not that high. This means that the scale is simply too small for a good improvement in efficiency. But for very large instances, gains are not that high, as FCEs with a certain size reach a good economy of scale on their own. Figure 3 shows that a larger number of cooperating companies achieve higher cost savings. In general, it can be said that joint route planning is more profitable for small transportation companies that collaborate with other companies.

The effect of the average order size shows that sectors with typically smaller orders, like fashion or consumer electronics, can take more profit from joint route planning than sectors with larger order sizes, like wood and paper, for example. Another factor that has been analyzed is time windows.

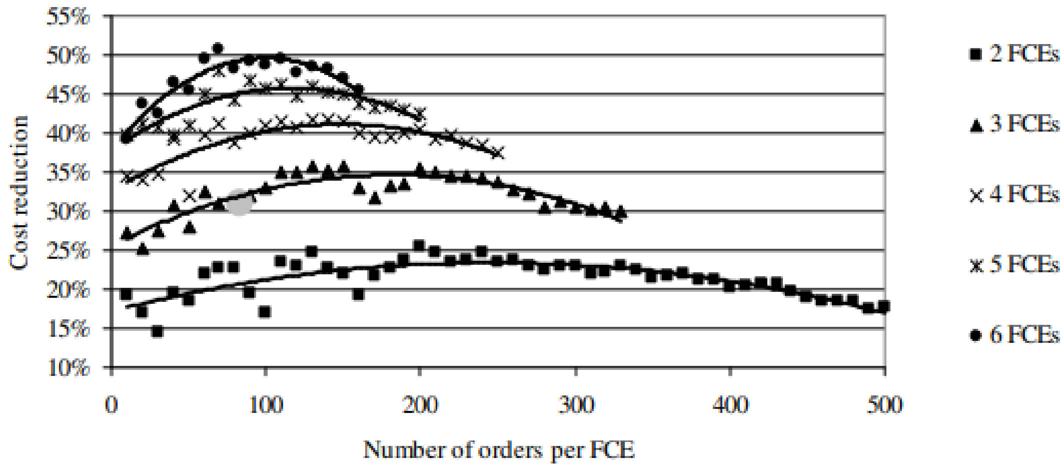

Figure 3: Impact of number of oders per company on cost reduction
Cruijssen et al. (2007)

While small-time windows restrict the solution space too much, big-time windows enable companies to combine many orders and therefore already have efficient transportation routes when acting alone. The biggest cost savings can be achieved for problems with time windows of average duration. A factor indicating the potential savings for the service network design is the size of the distribution area, which can be seen in figure 4. As service network design usually covers bigger areas, the fact that bigger regions tend to have bigger cost savings than local regions is quite promising for this work. More synergy values can be reached if the order size between the companies is quite similar. All summed up, it can be said that the most potential of joint vehicle routing planning can be achieved in a setting with a large number of companies that are of a similar size and are not too big, with goods being produced that are typically of small order sizes compared to the truck capacity, with rather narrow time windows, and with a service area consisting of large distances.(Cruijssen et al., 2007)

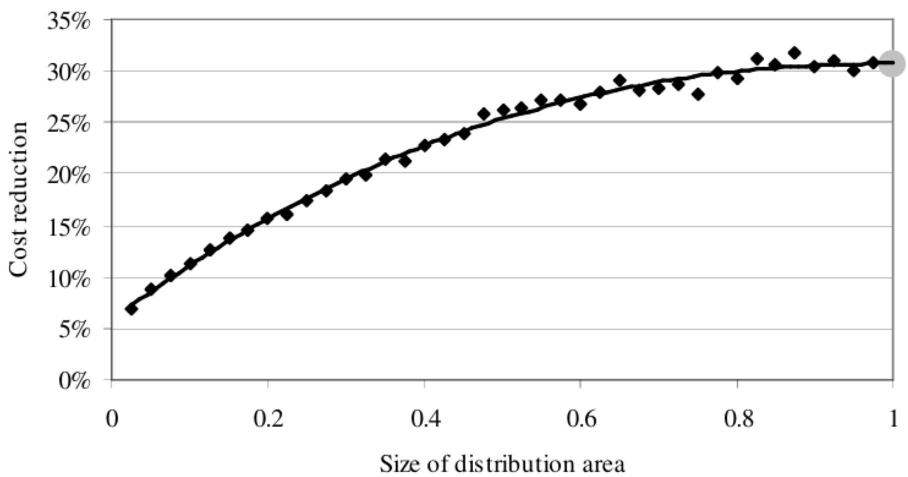

Figure 4: Impact of size of distribution area on cost reduction
Cruijssen et al. (2007)

An analysis of the possible advantages of cooperation for the vehicle routing problem (VRP) has already been conducted, demonstrating profit increases of about 20–30%. A positive side effect of saving costs and transportation routes is having less CO_2 emissions, which is an important topic in times of climate change. The potential reduction of CO_2 emissions has already been considered by Ballot and Fontane (2010). Besides production and other issues, freight transportation is a major contributor to CO_2 emissions. About 28% of the total CO_2 emissions in the EU can be traced back to freight transportation.

2.2 Service Network Design

2.2.1 Introduction to Service Network Design

Service Network Design is a subcategory of network design, which in general covers a variety of planning and operation issues in logistics, transportation, telecommunications, and production-distribution systems. Graphs are used to formulate a network design. These graphs include nodes and vertices, which are connected by links. Directed links are called arcs. (Crainic, 2000)

Speaking of service network design (SND), this usually refers to transportation systems. The aim is to make decisions in a way to satisfy the demand while ensuring high profitability for the company and achieving a certain level of quality standards and efficiency. Optimizing both is a difficult trade-off, as improving one aspect can have negative effects on the other. For example, reaching better customer service can be done by increasing the frequency of operating a given service. However, this could cause congestion at the terminals, and fewer resources are available for other services. The goal of service network design is to handle these problems across the entire network. Therefore, operating costs and service performance need to be measured and included in the objective function. Indicators for service performance would be the number of delays or some predefined performance targets, like an average delivery time.(Crainic et al., 2021)

Transportation problems can be divided into two levels. Freight needs to be transported to the customer. This is done in a local area and is usually modeled by variants of the vehicle routing problem with time windows or the pickup and delivery problem. One step before that, freight is usually transported from the customer's origin to an intermediate terminal, from where it is then shipped to the final destination. This level is considered to be a long-haul operation with inter-city or inter-regional movements and is therefore usually modeled as a variant of the service network design problem. A more detailed view of the differences between these two levels can be seen in figure 5. Location decisions have already been made, and customers have been assigned to a location. On the line-haul level, a product is shipped from the supplier to the intermediate terminal, which is defined as a breakbulk. At the distribution level, each breakbulk has a distinct customer group that is provided straight from it. This work will focus on the second mentioned level, with a supplier location as its origin and a customer-associated terminal (breakbulk) as its destination. These destination terminals are used as depots, from which the products are distributed to customers.(Medina et al., 2019)

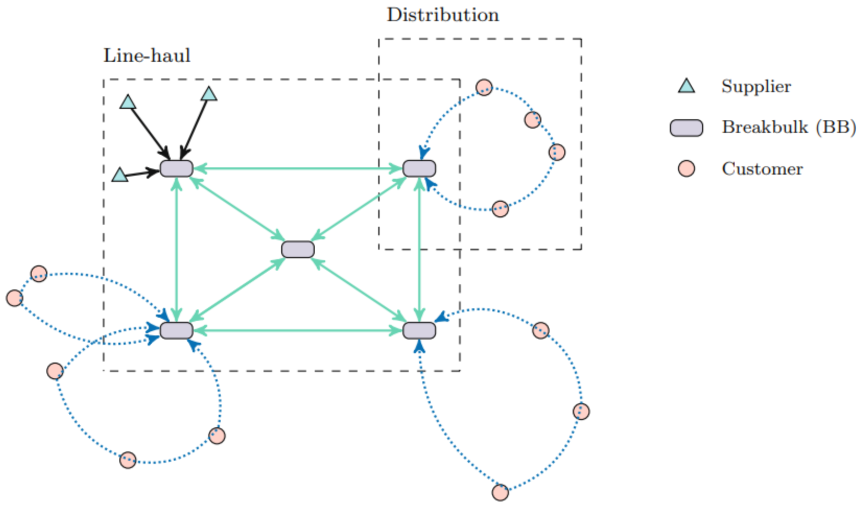

Figure 5: Multi-level transportation network
Medina et al. (2019)

The service of transporting some kind of goods from their origin to their destination happens in a given network. Vehicles or convoys are following a certain route in the network to execute these services. Some important features of each service are physical characteristics like vehicle type and capacity and operational characteristics like departure time, arrival time, trip duration, and costs. The two major decision sets are routes and schedules. While routes cover origin, destination, and intermediate terminals, schedules include if, when, and in which frequency services happen, as well as the sequences of services, terminals, and operations to move goods. Another helpful indication feature is the cut-off time, which can be defined as the latest possible time when the carrier needs to depart. This might be included in the schedule. A large part of service costs consists of the costs of vehicles and power units that are used for transport. Therefore, it is very important to ensure cost reductions through economies of scale in capacity utilization by applying an efficient and suitable schedule. Additional cost reductions should be achieved through collaboration with other companies, which are shown at a later point in this work. (Crainic et al., 2021)

Freight transportation can be described as the efficient movement of goods and is a significant part of the total cost of a product. These products, which are either raw materials or finished goods, can be moved by truck, train, plane, ship, or any combination of those modes. Service network design usually deals with consolidated freight transportation. In this situation, freight from different customers is transported by vehicles or convoys to possibly different origins and destinations. The external side of this process is that some services are put together in a schedule, consisting of the departure and arrival times as well as the stops made on the route. Internally, an operational plan is made, including rules and policies that have an effect on the complete system. In contrast to so-called "door-to-door" operations performed by truckload motor carriers, consolidation operations are more of a transportation by multiple vehicles. These convoys usually operate between terminals, where products are not only consolidated but grouped or simply moved between different services. Terminals are used for loading, unloading, and transshipping products. The goal is always to satisfy demand while operating in an efficient way. Service network design has the object of building services that reach those goals using a large number of vehicles. Also, convoys can be formed, which can then be disaggregated at the terminals, moving vehicles between different convoys. Terminals are also used for unloading and reloading at different stops along the route. Another problem that needs to be faced in service network design is the repositioning of empty vehicles, as imbalances of vehicles occur due to trade flows.(Crainic, 2000)

The following classifications are made considering transportation planning levels, different possibilities of handling shipments, and necessary decisions that have to be made.

Planning levels: Transportation planning is usually divided into three levels.

- Strategic (long term): General decisions like the positioning of the terminals.
- Tactical (mid term):The design of the service network is considered as a tactical decision.
- Operational (short term): This includes deploying schedules as well as the routing of vehicles.

Service network design is mainly considered tactical, but depending on the firm's horizon, the planning level could be classified as strategic/tactical or tactical/operational.

Shipment strategies: Shipment between two terminals can be done in many different ways and is therefore a very complex problem. Some strategies that can be used are:

- Consolidation with other shipments and direct transfer from the origin to the final destination terminal.
- Consolidation with other shipments and transfer from the origin to the final destination, but with intermediate terminals for drop-off and delivery of other shipments.
- Consolidation for an intermediate terminal. From this point on, it is reclassified to be finally shipped to the desired destination.
- Put the shipment on a direct dedicated service, only leaving if a certain volume is reached. Consumer contracts and the latest possible arrival times need to be considered to ensure that this strategy is even possible.

The best option depends on the specifics of the situation. Option one only makes sense if the frequency is high enough for direct transfers. Otherwise, it would be better to make use of intermediate terminals like in option two, which would raise utilization and minimize waiting time at the original terminal until being shipped and therefore result in a probably earlier arrival time. But this option also has its disadvantages, like additional effort for unloading and reloading, resulting in more delays and congestion at the intermediate terminals. Because the entire network must be taken into account, optimizing for a single cargo will not yield the best overall result.

Decision categories: For the best outcome, every choice must be taken into account and optimized as a whole. These decisions cover:

- Service selection: which routes should be offered and what are the characteristics of the service (scheduling decisions).
- Traffic distribution: routes and services used, including intermediate terminals and corresponding operations.
- Terminal policies: Specifying what happens in the terminals.
- Empty Balancing Strategies: Repositioning of Vehicles. (Crainic, 2000)

2.2.2 Standard SND Models

After giving an introduction to the topic, some forms of the service network design problem with the following properties are now introduced. The goal of this problem is to minimize the total transportation costs while finding a feasible assignment for each commodity. This means that paths need to be created that bring the commodities from their origin to their destination within a certain time span. On a tactical planning level, carriers should find the optimal paths through the network.(Boland et al., 2019)

One of the early problem formulations of service network design was done by Crainic and Rousseau (1986). In their work, they used the frequency of services as a decision variable. A simplified version of the original approach can be found in Crainic (2000) to show the main challenges of this problem. The model is defined on a physical network G = (N,A), on which the carrier operates, and can be written as:

(B1) $Min \sum_{s \in S} \Psi_s(y) + \sum_{p \in P} \sum_{l \in L^p} \Phi_l^p(y,h) + \Theta(y,h)$
subject to:
(B2) $\sum_{l \in L^p} h_l^p = w^p, \qquad p \in P$
(B3) $y_s \geq 0$ and integer, $\qquad s \in S$
(B4) $h_l^p \geq 0, \qquad l \in L$ and $p \in P$

Sets used:
$T \subseteq N$: selected nodes of the node set to be terminals
S: set of services s with route r_s
$T_s \in$ T: includes all terminals (origin, destination, intermediate stops) on the route of service s
Π_s: set of service legs. π_{sk} is a service leg, which can be explained as a sub-path of the service route r_s. A service leg is the path between two consecutive terminals.
P: set of products p
L^p: set of itineraries l of product p
T_{lp}: includes all terminals (origin, destination, intermediate stops), where operations are performed

Parameters used:
Θ_s: the service class could yield for example the following characteristics: mode, restrictions, service priority and traffic preferences
u_{sk}: capacity on service leg π_{sk}; $\quad u_{sk} = min_{(i,j)\in\pi_{sk}}\{u_s, u_{ij}^{\Theta_s}\}$
u_s: capacity of service s
$u_{ij}^{\Theta_s}$: maximum load of a service of category Θ_s from i to j.
w^p: Number of vehicles needed to move product p, with p including information about commodity type, origin and destination. This means the demand is given in number of vehicles.

Decision variables used:
y_s: service frequency, $\quad y = \{y_s\}$ is the corresponding vector
h_l^p: volume of product p using itinerary l, $\quad h = \{h_l^p\}$ is the corresponding vector.

Objective function and constraints:
The first part of the objective function (B1) describes the total operational costs of services. The middle part represents the costs of moving product p using itinerary l. In the last part, penalties are added, considering various restrictions like capacity or time. Constraint (B2) is making sure that the total volume of product p over all itineraries l equals the volume needed to move the product. Constraints (B3) and (B4) restrict the decision variables for the service frequency and the volume of product p on itinerary l to positive values. Additionally, the service frequency needs to be an integer, as a service can either be done or not, but not partially.(Crainic, 2000)

A more modern model of the service network design problem by Boland et al. (2019) is shown in the following: This time, the decision variable covers if a certain commodity is dispatched on an arc instead of the service frequency. Also, not only the volume of a single product on an itinerary but the whole dispatched quantity per arc forms a decision variable.

(C1) $C(\Delta) = Min \sum_{k\in K}\sum_{a\in A_\tau} v_a q^k x_a^k + \sum_{a\in A_\tau} f_a z_a$
subject to:

$$(C2)\ \sum_{a\in\delta_k^+(n,t)} x_a^k - \sum_{a\in\delta_k^-(n,t)} x_a^k = \begin{cases} 1 & if \quad n=o^k, t=\lceil e^k/\Delta \rceil \\ -1 & if \quad n=d^k, t=\lfloor l^k/\Delta \rfloor \\ 0 & if \quad otherwise \end{cases} \quad \forall k\in K, (n,t)\in N_\tau$$

$$(C3)\ \sum_{k\in K} q^k x_a^k \le u_a z_a, \quad \forall a\in A_\tau$$

$$(C4)\ x_a^k \in [0,1], \quad \forall k\in K, a\in A_\tau$$

$$(C5)\ z_a \in Z_+, \quad \forall a\in A_\tau$$

Sets used:
N_τ: set of nodes n
A_τ: set of arcs a
τ: time points
K: set of commodities k
$\delta_k^-(n,t)$: set of ingoing arcs
$\delta_k^+(n,t)$: set of outgoing arcs

Parameters used:
τ_a: costs of arc a
v_a: costs per quantity on arc a
f_a: fixed costs per transfer on arc a
u_a: capacity on arc a
o^k: origin of commodity k
d^k: destination of commodity k
q^k: size of commodity k
e^k: time commodity k becomes available
l^k: latest possible time commodity k has to be at destination

Decision variables used:

$$x_a^k = \begin{cases} 1 & \text{if commodity k} \in \text{K dispatches on arc a} \in A_\tau \\ 0 & \text{otherwise} \end{cases}$$

z_a : integer quantity of all dispatches on arc a $\in A_\tau$

Objective function and constraints:

The objective function (C1) aims at minimizing the total costs, which consist of the variable quantity-dependent costs and the fixed costs per transfer. In the flow constraint (C2), each commodity has to leave its origin after becoming available and reach the destination before the latest possible arrival time. Consolidation constraint (C3) makes sure that if commodities are at the same arc at the same time, they need to be dispatched together in multiples of the capacity ($u_a * z_a$). Constraint (C4) defines that x_a^k can only be one (if commodity k dispatches on arc a) or zero (otherwise). Constraint

(C5) defines that the dispatched quantity on an arc has to be an integer and positive.

Comparing the two models from above, some overlaps but also discrepancies can be seen. In the following, the first mentioned model from Crainic (2000) is referred to as model B, and the approach made by Boland et al. (2019), which was the latter model to be explained, is model C. Using timed arcs, time can be taken into account explicitly in model C, rather than frequency in model B. In addition to the fixed and variable costs, model B integrates several restrictions in the objective function as a penalty term. However, it is not clear how exactly this penalization should work. In model C, an additional constraint is used to prevent exceeding capacity. All in all, model C gives a more detailed and better idea of what should be optimized and under which conditions. Therefore, the further work is more referring to the model of Boland et al. (2019).

2.2.3 Further developments of SND

For the vehicle routing problem, there are already multiple papers about collaborative planning, but in service network design, this still needs to be explored. SND is done at the tactical planning level and covers aggregated transport amounts between fixed locations over bigger areas, compared to single orders and different locations in vehicle routing. Time can be discretized to reduce the size of the solution space because this is a very complex issue that is difficult to solve for larger instances. If more commodities, or more nodes are involved, the solution space increases very fast. Taking model B from above as an example, it can be seen that for each arc additional decision variables are necessary. More nodes follow more arcs and, therefore, more decision variables. Therefore, the planning horizon is partitioned into discrete time periods, like, for example, one- or multiple-hour intervals. It is common to use uniform time intervals. One needs to consider that discretization is necessary for big problems but goes along with a loss of quality. Short-term intervals, which are relatively close to the continuous time problem, have a smaller loss of quality than bigger intervals, but bigger intervals are computationally more tractable. Despite concentrating on solution quality, it is important that problems are solvable within an acceptable amount of time. This trade-off needs to be considered when choosing the length of the time interval, as the size of the program and the quality of the solution are directly influenced by this decision. Empirical results in Boland et al. (2019) showed that the relative gap between the optimal solutions of the discrete and the continuous models can be up to 20%. In figure 6 the standard deviation of the cost increase is marked by the shaded area and tested instances are grouped by the length of the time intervals and a grade of flexibility. Commodities with bigger differences between their earliest (depending on availability and transportation time) and latest (due date) possible arrival times are considered more flexible. Such flexible commodities should be more resistant to discretization than "inflexible" ones.

Following discrete time intervals, rounding schemes for the time windows and the travel time need to be implemented. This is necessary since all time-related factors need to be properly mapped. There

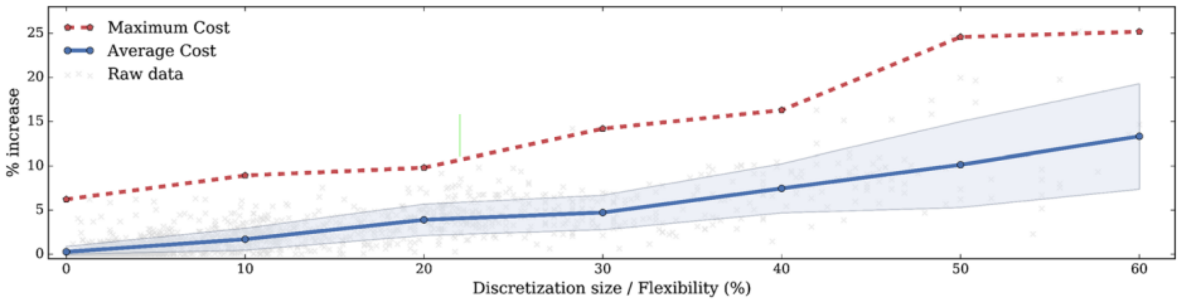

Figure 6: Impact of discretization on cost increase
Boland et al. (2019)

are three ways to round: regular, optimistic, and conservative. In conservative rounding, all time windows get smaller and the travel times get bigger. The opposite happens in optimistic rounding (bigger time windows, smaller travel times). For regular schemes, values are rounded to the nearest value. Every solution with conservative rounding is a guaranteed feasible solution to the continuous time problem. Regarding the other two methods, this cannot be stated. As a result, the only choice that needs to be taken into account is conservative rounding.(Boland et al., 2019)

Another goal of service network design is to find a trade-off between route circuitry and capacity utilization. The fastest service is provided by using the shortest route, which increases customer satisfaction but comes at a high cost because less capacity is used. By considering a different (longer) route and grouping shipments together, it is possible to utilize more capacity, which reduces the number of truck miles and, consequently, the cost of transportation. It should be mentioned that, for simplification reasons, transportation times are always considered to be fixed, which is not the case in the real world. Boland et al. (2019) mention that stochastic models need to be considered but are rarely used due to the current possibilities for solving such problems.

In the paper of Pedersen et al. (2009) an extension on service network design is presented, including asset repositioning and utilization. These important additional constraints, considering vehicle movements, are referred to as "design-balanced constraints." Therefore, the model is called the design-balanced capacitated multicommodity network design model (DBCMND), which is a generalization of the capacitated multicommodity network design model (CMND). The main problem with service network design is selecting services and their schedules in a way to satisfy the demand within their time windows while minimizing costs. Besides that, the availability of route assets needs to be checked, which are needed at the terminals to perform the services. Pedersen et al. (2009) consider only one asset type and use one unit of an asset per service. This asset could be either a crew, cars, ships, engines, trucks, etc. A clearer grasp of the issue should be provided by figure 7, which shows a tiny example of a cyclic servicing schedule with three terminals over a one-week time horizon. In this time-space diagram, arcs between the terminals represent possible transportation routes. Vehicles or goods could remain in a waiting state at the same terminal. This is represented by the horizontal lines in each terminal. Arcs that are going backward in time are used for services that go over two different weeks. For example, the arc from terminal one on day seven goes to terminal three on day one of the following week. Services that go over more than one planning period are a sign of schedule repetition, which is used quite often in the real world. The best example would be public transportation systems, which use more or less the same transportation schedule every week.

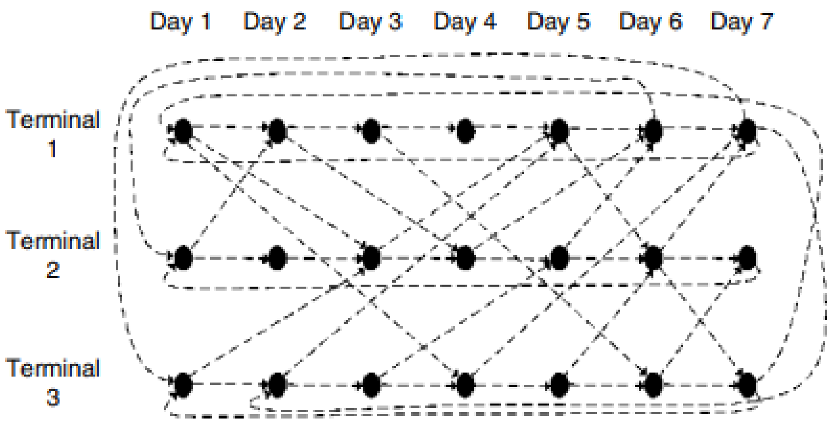

Figure 7: Time-space diagram for cyclic service schedule
Pedersen et al. (2009)

The decision variables in Pedersen et al. (2009) are formulated a little bit differently than in Boland et al. (2019). The integer variable in Boland et al. (2019) was representing the whole quantity of all services dispatched on an arc, and the binary variable x_a^k was used to determine if commodity k dispatches on arc a (=1) or not (=0). In Pedersen et al. (2009) a continuous variable was used for the flow quantity per commodity moved by a service. and $y_i j$ indicates if arc i,j is opened (=1) or not (=0). The additional flow distribution constraint in the DBCMND model of Pedersen et al. (2009) can be formulated as:

$$\sum_{j \in N^-(i)} y_{ij} - \sum_{j \in N^+(i)} y_{ji} = 0, \qquad \forall i \in N$$

Each terminal needs at least the same number of vehicles available as required. The flow distribution constraints make sure that incoming vehicles equal outgoing vehicles at every terminal. An example of node unbalance can be seen in figure 8, with one incoming and two outgoing arcs in the left node and two incoming but no outgoing arcs in the right node. Flow balance constraints prevent this from happening.

Coming back to the time space diagram, figure 9 shows a simplified version of a feasible vehicle rotation with only one vehicle but no violations of flow balance constraints. The vehicle tour starts on day three at terminal 3, travels to terminal 1 on day five, terminal 2 on day six, terminal 1 on day seven, and ends back at terminal 3 on day three.

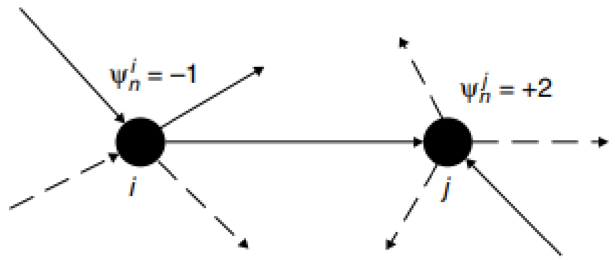

Figure 8: Node unbalance
Pedersen et al. (2009)

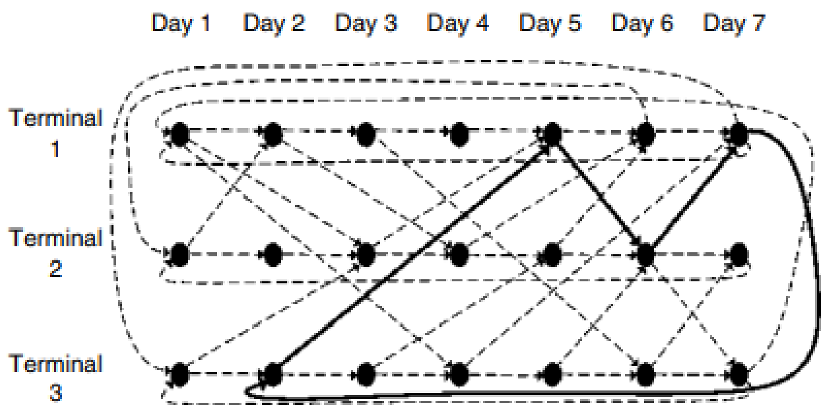

Figure 9: Feasible vehicle rotation
Pedersen et al. (2009)

The work of Andersen et al. (2009) focuses on enhancing the integration of vehicle management and coordinating multiple fleets in the context of service network design. Services provided by their own company are termed "internal services", but the exchange and coordination with other systems, which are referred to as "external services and networks", are taken into account. Services are generally defined as responding to demands with specific origin and destination characteristics. Given that capacity is limited, demands can be met by one or multiple services. Demands should ideally be delivered as soon as possible, but it's common for them not to be available for immediate shipment.

Services possess key attributes, including priority, speed, and capacity. A "service leg" is defined as a consecutive pair of terminals visited by a service. It's possible for a service to encompass one or multiple service legs. Since planning is a collaborative effort with a focus on overall performance, the system can be viewed as centralized. To operate all selected services within a subsystem, assets are required. These assets have the flexibility to be repositioned and used at different terminals, not only at the destination terminal of the last service. The challenge at hand encompasses the selection of internal services and the determination of their corresponding departure times. This involves the coordination of designated vehicle fleets to meet the requirements of the chosen services and the optimization of routes for transporting specified demand from its point of origin to its destination. The objective is to minimize the total transit time of this demand within the system while efficiently utilizing intermodal resources and the selected internal services. Additional complications are the limited frequency of departures and the need for a repetitive schedule. Traditional service network design models normally use fixed costs for each operated service and variable costs depending on whether a demand flows over a certain arc (flow costs).

Andersen et al. (2009) define their model over a given planning horizon, which is typically one week or one month long. This time period is further divided into smaller intervals, usually one or more hours or one or several days. Every demand has a specific window within it can be transported from a given node. A major decision for the problem is to choose the right time interval for the departure of some goods. It is assumed that services leave a node and arrive at a node at the beginning of a time period. Moreover, services enter and exit intermediate terminals within the same time frame because stopping, loading, and unloading are all regarded as part of the service time. New services can be operated by vehicles once they arrive at the corresponding node, and cargo can be transported further as soon as it has arrived at a node.

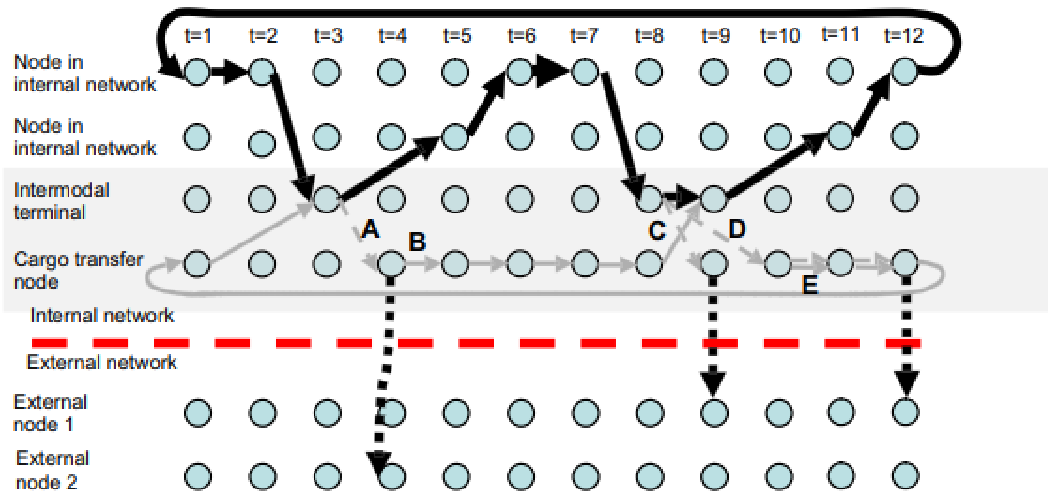

Figure 10: Time-space representation of intermodal operations
Andersen et al. (2009)

Figure 10 represents the exchange of goods between an internal and external network. Each terminal has one node per time period. The so-called intermodal operations happen at cargo transfer nodes at intermodal terminals, where cargo waits to be transferred. Black solid arcs depict internal and black dotted arcs external services. While solid gray arcs represent flow from external to internal services, dotted arcs are used for the other way around. A-E are different demands. For example, demand B gets available at the cargo node either because this is the demand's origin or it comes from an external service. This demand is held at the cargo node until time period eight and is further transferred to the intermodal terminal in time period nine, as one time period is required for loading. Loading times are specific to the demand and could require multiple time periods. Finally, demand B uses the internal service, which is leaving the intermodal terminal at time period nine. The collaborative approach in this thesis could make use of the strategy that uses multimodal terminals to connect terminals of the internal and external networks. In this context, intermodal terminals could be used to connect the networks of different companies and therefore would work as reloading terminals for exchanging goods. The fact that Andersen et al. (2009) emphasize that operators should concentrate on synchronization and developing strategic partnerships with others is another positive factor for focusing on the impact of collaboration in this thesis.

Wu et al. (2023) examine service network design with hub capacity constraints for same-day delivery. Although hub capacity is not considered in the model of this master thesis, the paper of Wu et al. (2023) adds further important knowledge as the planning horizon is similar, which gives a better idea of the characteristics of the problem instances. Furthermore, same-day delivery becomes more and more important for package carriers in urban areas. A prerequisite for a successful company in such conditions is the consolidation of shipments, for which hub networks are needed. Due to the high facility prices in or near cities, it is a reasonable assumption that locations are not very big, and therefore capacity is limited not only for storing goods but for vehicles to be managed at the same time.

The test instances in Wu et al. (2023) are based on real-world instances in one of China's megacities, operated by a company called SF Express. The demand is represented by a set of commodities with the following properties: origin hub, destination hub, number of packages, and the available time (origin) as well as the due time (destination) of the commodity. A homogeneous fleet with a capacity of 400 packages per truck is assumed. It can happen that various commodities have the same origin and destination but differ in availability and/or due dates. As the hub capacities are limited, there is a maximum number of possible departures (loadings) and arrivals (unloadings) at the same time for each hub. Every loading and unloading process is considered to take ten minutes.

The instances in the paper of Wu et al. (2023) are solved by heuristic approaches. Therefore, in contrast to this master thesis, it is possible to use much larger problem instances. The four different instances in Wu et al. (2023) cover 270–1779 commodities, with a planning period of at least 2.5 hours and up to 5.6 hours. Examining the smallest of the four problem occurrences in further detail reveals the following characteristics: The already-mentioned 270 commodities over a planning horizon of 2.5 hours show an average of 32 packages per commodity with a relatively high standard deviation of 28. The time when commodities become available differs by 15 minutes on average. In this problem, the average time of commodities becoming available is 13:09, without a concrete starting and ending time of the planning horizon being mentioned. The average due time is 15:02, with a standard deviation of eight minutes. From this, it follows that the time window for a commodity is, on average, a little bit less than two hours. Certain information is required for the network as well as the demand. In this particular problem instance, the network consists of 17 hubs. Due to hub capacity constraints, a solution with all commodities served is no longer guaranteed, and therefore the upper bound for served commodities in this problem is 264. The average (43 minutes, 25 kilometers) and standard deviation (14 minutes, 13 kilometers) are given for the travel time as well as for the travel distance. The loading and unloading capacities are fixed to a maximum of three vehicles that can load at the same hub simultaneously and four vehicles that can unload their freight.

The just-presented instances guide the development of the instances for this master thesis. It should be remembered that the instances in the thesis are restricted to a certain size, as an exact approach is used for solving the problem, in contradiction to the heuristic approaches used in the paper of Wu et al. (2023).

Similar to Wu et al. (2023), He et al. (2022) cover service network design problems with hub capacity constraints. They present an exact algorithm with dynamic discretization that is able to solve small to midsize instances to optimality in a reasonable amount of time.

Certain types of collaborative techniques are already in use in practice. Turvo, for example, is a company that promises collaborative logistics for shippers. They mention that shippers profit from multiple advantages through collaboration with Turvo, such as lower transportation costs, improved capabilities, and end-to-end visibility combined with increased efficiency. The benefits of using Turvo aren't quantified in hard data, such as a specific reduction in transportation expenses up to a predetermined level. Although it is not completely clear how this collaboration works, it can be seen that the idea of combining the capabilities of multiple companies has already somehow been implemented in the real world.(Turvo, 2023)

3 Collaborative Service Network Design

Drawing on the knowledge gained from the previous chapter, the following sections give a detailed description of the problem **(3.1)** and introduce the resulting mathematical formulation of both the collaborative and non-collaborative models **(3.2)** .

3.1 Problem Description

The collaborative service network design model combines the resources of multiple companies with the goal of taking advantage of this collaboration. In a more concrete way, synergizing the fleets and terminals of companies should raise transportation efficiency and consequently save costs. The problem is formulated over a certain planning horizon, divided into discrete time intervals, where commodities need to be shipped from their origin to their destination node. Discrete time intervals are used to restrict the solution space to a smaller number of possible solutions, making the problem applicable to a larger set of nodes and commodities. These commodities are assigned with different sizes and transferred by trucks, which only have a restricted capacity. Additional information on commodities includes the origin and destination nodes as well as the corresponding company, the time the commodity becomes available at the origin node, and the latest possible arrival time at the corresponding destination node. Shipments are operated within a certain network, consisting of a set of nodes, which are called terminals, and the travel time and distance between those terminals. As the instances are not from a real-world data source, the time between the nodes is calculated in direct relation to the distance. Collaborative service network design has the idea of gaining transportation efficiency by enabling companies to reload shipments. From this, it follows that additional time for reloading must be considered for this problem. Figure 10 can be taken as inspiration for the reloading process. Instead of intermodal terminals between internal and external services, these can be seen as intermodal terminals between different companies. Due to simplification reasons, instead of adding additional time due to reloading, costs for a reloading process are added directly. A reasonable cost value for that process is discussed in the section **"Problem Instances"**.

The minimal transportation distance would be to deliver each shipment directly from its origin to its destination. In this case, the number of trucks would have to be equal to the number of shipments, but due to the high acquisition costs of trucks, it is more profitable to consolidate shipments and transportation routes. Moreover, for some node combinations, there might not be a direct connection, and an intermediate node has to be visited anyway. The collaborative approach is saving costs through a lower need for trucks due to more shipment consolidation possibilities. Although the transportation distances and therefore the variable transportation costs are higher compared to direct shipments, there is a significant cost improvement considering the lower fixed costs for trucks. The objective function minimizes the overall costs. The variable costs per transportation distance, the costs for a reloading process, and the fixed costs for using a truck are formulated in the objective function. There is no need to restrict the number of trucks because a smaller number of trucks is a desired goal.

The exact properties of every problem instance can be seen in the corresponding section, **"Problem Instances"**, which will follow in the next chapter, **"Computational Study"**. The number of commodities and time intervals are the most influential factors, considering the size of the problem in terms of computation time. It is desirable to use a large set of commodities and terminals that yield significant results. Therefore, time discretization is an important feature to restrict the solution space and ensure a reasonable computation time.

Some constraints are needed to make the problem feasible. The flow conservation constraints make sure that commodities only leave their origin after becoming available and only arrive before the latest possible arrival time. For intermediate nodes, the arrival of a certain commodity always should be before the departure of the same commodity from this node. However, in the time-expanded problem, it is possible that arrival and departure happen in the same time period. It is necessary to define a constraint that ensures the consolidation of shipments if they are in the same arc at the same time. In this case, these shipments need to be transferred together in multiples of the capacity. These constraints are called the consolidation constraints. A decision variable is used to decide whether a commodity dispatches on a certain arc or not within a certain time period. This variable should only take binary values. More concretely, if commodity k dispatches on arc a (from node i to j), from time period s to e, the corresponding variable is one and zero otherwise. A second type of decision variable defines the integer quantity of trucks that are dispatched over a corresponding arc. This should only take positive integer values. A violation of any of those constraints would make the solution infeasible. In the next section, **"Mathematical Model"**, a closer look is taken at the just-mentioned constraints.

To give an idea of a different solution approach for collaboration, a different but more complex approach would be to create a two-level problem. Taking figure 5 in Section 2.2.1 as an inspiration, the nodes of all companies could be grouped into different areas. The first problem would be to move goods to the entry points of the corresponding area of the destination terminal. The second step would be similar to the VRP approach, bringing all goods from the entry points of an area to their destination terminal. Due to the rising complexity of using two levels, this approach will not be further considered, but it should give inspiration for different possibilities of solving this problem.

3.2 Mathematical Model

Two mathematical models are created, one for the collaborative approach and one for the non-collaborative approach. Both models contain the objective function of aiming for minimum costs and all constraints that are necessary to get a valid model. Costs are calculated as the sum of the time and distance needed to deliver commodities, the fixed costs for using trucks, and the arising costs for the reloading process if commodities are shipped together. For the reloading of goods, additional time and distance are considered. Reloading is only done if costs are saved. Otherwise, the commodities are shipped alone. Therefore, the objective function value of the collaborative model cannot be higher than that of the non-collaborative model. If a combined shipment of freight from different companies would not decrease costs for any commodity, the collaborative model would have the same solution as the non-collaborative model.

It needs to be decided which service is done by which company in what time interval (leaving and arriving). For each commodity, the origin and destination location/terminal are known, as is the amount of goods that need to be shipped (multi-commodity flow). The additional costs of reloading are known, as are the goods initially shipped by which company.

The foundation of the following mathematical model is taken from the model in the work of Boland et al. (2019). Due to the new collaborative approach, some expansions have to be made. The model where all companies combine their fleet, which means that shipments from different companies can be transshipped together, is further referred to as the collaborative model. The non-collaborative approach, where each company is dealing with their shipments on their own, is further referred to as the non-collaborative model. After introducing the two models, the differences are made clear.

Collaborative model:

(D1) $C(\Delta) = Min \sum_{c,k\in K}\sum_{i,j\in N}\sum_{s,e\in T} v_{ij}q^k x^{ck}_{ijse} + \sum_{i,j\in N}\sum_{s,e\in T} f_{ij}z_{ijse} + r * (\sum_{c,k\in K}\sum_{i,j\in N}\sum_{s,e\in T} x^{ck}_{ijse} - \sum_{i,j\in N}\sum_{s,e\in T} z_{ijse})$

subject to:

(D2) $\sum_{c\in K}\sum_{i\in N}\sum_{s,e\in T} x^{ck}_{jise} - \sum_{c\in K}\sum_{i\in N}\sum_{s,e\in T} x^{ck}_{ijse} = \begin{cases} 1 & if \quad j = o^k \\ -1 & if \quad j = d^k \\ 0 & if \quad otherwise \end{cases} \quad \forall k \in K, j \in N$

(D3) $\sum_{s1\in T} x^{ck}_{ijs1e1} + \sum_{e2\in T} x^{ck}_{jhs2e2} <= 1 \quad if \quad s2 < e1 \ \ and \ \ i \neq j \quad \forall (c,k) \in K, (i,j,h) \in N, (s2,e1) \in T$

(D4) $x^{ck}_{ijse} = 0 \quad if \quad c \neq c_k(k) \quad or \quad e \neq s + v_{ij} \quad \forall (c,k) \in K, (i,j) \in N, (s,e) \in T$

(D5) $x^{ck}_{ijse} = 0 \quad if \quad s < e_k(k) \quad or \quad e > l_k(k) \quad \forall (c,k) \in K, (i,j) \in N, (s,e) \in T$

(D6) $\sum_{c,k\in K} q^k x^{ck}_{ijse} \leq u_{ij}z_{ijse}, \quad \forall (i,j) \in N, (s,e) \in T$

(D7) $x^{ck}_{ijse} \in [0,1], \quad \forall (c,k) \in K, (i,j) \in N, (s,e) \in T$

(D8) $z_{ijse} \in Z_+, \quad \forall (i,j) \in N, (s,e) \in T$

Sets used:
K: set of commodities
N: set of nodes
T: set of time periods

Parameters used:
f_{ij}: fixed costs per transfer on arc from node i to j
u_{ij}: capacity on arc from node i to j
v_{ij}: costs per quantity on arc from node i to j (symmetric)
o^k: origin of commodity k
d^k: destination of commodity k
q^k: quantity of commodity k
e^k: earliest possible time commodity k can leave
l^k: latest possible time commodity k has to be at destination
c^k: each commodity k belong to a company c

Decision variables used:
x_{ijse}^{ck} : binary decision variable if commodity k of company c dispatches on arc from node i to j from time period s to e (=1) or not (=0)
z_{ijse} : integer quantity of all trucks dispatching on arc from node i to j from time period s to e

Objective function and constraints:
The objective function (D1) aims at minimizing the total costs, which consist of the variable quantity-dependent costs, the fixed costs per transfer, and the reloading costs. The variable quantity costs depend on the transportation distance and the transported quantity of each commodity. A predefined value of fixed costs is only added if the corresponding arc from node i to j is used in a certain time period from s to e. The last part of the objective function refers to the reloading costs. Each time an intermediate node is used, this counts as a reloading process and therefore causes reloading costs r. The number of intermediate stops can be calculated as the difference between all used arcs per commodity and time interval ($x_{ijse}^{ck} = 1$) and all used arcs in general ($z_{ij} > 0$). The remaining value represents the sum of all arcs that have been used by more than one commodity at the same time, which is equal to the total number of reloadings.

In the flow constraint (D2), the origin of each commodity needs to have one more outgoing than in-going arc, and the destination of the commodity needs to have one less outgoing than in-going arc. All other nodes should have the same number of arriving and departing arcs for a commodity. This has to hold for each commodity. Constraint (D3) ensures that a commodity can only leave an intermediate node at a time point s2 that is bigger or equal to the arrival time e1 at this node. Holding arcs (i=j) do not have to be considered here, as this only affects arcs that leave the node. Constraints (D4) and (D5) restrict the decision variable x_{ijse}^{ck} in different ways. In (D4), the decision variable can only be positive if the commodity-company pair exists and if the arrival time is equal to the starting time of the commodity plus the travel time of the used arc. This makes sure the commodity needs exactly v_{ij} time periods to go from node i to j. The implementation of constraint (D4) is not necessary, as this is fulfilled automatically by the created decision variables. Before running the problem, the set of decision variables is restricted in such a way that those decision variables that should be 0 anyway are not created and therefore are set to 0. This is an important step for saving computation time and is further discussed in the subsection **"Implementation"** in chapter **"Computational Study"**. Constraint (D5) ensures that each commodity leaves its origin after becoming available and arrives at its destination before the latest possible arrival time. All decision variables that are not excluded by the constraints (D4) and (D5) could still be zero but also one. The important thing about these constraints is to prevent decision variables from being positive when they should be 0 to get a feasible solution. Consolidation constraint (D6) makes sure that if commodities are at the same arc at the same time, they need to be dispatched together in multiples of the capacity ($u_{ij} * z_{ijse}$) if the capacity of one truck is not enough. Therefore, the quantities q^k of all commodities of all companies (in the collaborative model) that go from node i to j from time period s to e are summed up. The total transported quantity needs to be smaller or equal to the truck capacity times the number of trucks used. Constraint (D7) defines that x_{ijse}^{ck} can only be one if commodity k of company c dispatches on arc from node i to j from time period s to e. For all other cases, the decision variable takes the value 0. Constraint (D8) defines that the dispatched quantity of trucks on the arc from node i to j from time period s to e has to be an integer and positive.

Non-collaborative model:

(E1) $C(\Delta) = Min \sum_{c,k \in K} \sum_{i,j \in N} \sum_{s,e \in T} v_{ij} q^k x_{ijse}^{ck} + \sum_{c \in K} \sum_{i,j \in N} \sum_{s,e \in T} f_{ij} z_{ijse}^{c} + r * (\sum_{c,k \in K} \sum_{i,j \in N} \sum_{s,e \in T} x_{ijse}^{ck} - \sum_{c \in K} \sum_{i,j \in N} \sum_{s,e \in T} z_{ijse}^{c})$

subject to:

(E2) $\sum_{c \in K} \sum_{i \in N} \sum_{s,e \in T} x_{jise}^{ck} - \sum_{c \in K} \sum_{i \in N} \sum_{s,e \in T} x_{ijse}^{ck} = \begin{cases} 1 & if \quad j = o^k \\ -1 & if \quad j = d^k \quad \forall k \in K, j \in N \\ 0 & if \quad otherwise \end{cases}$

(E3) $\sum_{s1 \in T} x_{ijs1e1}^{ck} + \sum_{e2 \in T} x_{jhs2e2}^{ck} <= 1 \quad if \quad s2 < e1 \;\; and \;\; i \neq j \quad \forall (c,k) \in K, (i,j,h) \in N, (s2,e1) \in T$

(E4) $x_{ijse}^{ck} = 0 \quad if \quad c \neq c_k(k) \quad or \quad e \neq s + v_{ij} \quad \forall (c,k) \in K, (i,j) \in N, (s,e) \in T$

(E5) $x_{ijse}^{ck} = 0 \quad if \quad s < e_k(k) \quad or \quad e > l_k(k) \quad \forall (c,k) \in K, (i,j) \in N, (s,e) \in T$

(E6) $\sum_{k \in K} q^k x_{ijse}^{ck} \leq u_{ij} z_{ijse}^{c}, \quad \forall c \in K, (i,j) \in N, (s,e) \in T$

(E7) $x_{ijse}^{ck} \in [0,1], \quad \forall (c,k) \in K, (i,j) \in N, (s,e) \in T$

(E8) $z_{ijse}^{c} \in Z_+, \quad \forall (c) \in K (i,j) \in N, (s,e) \in T$

Differences to the collaborative model can be found in the objective function (E1) as well as in the constraints (E6) and (E8). These parts of the model consider the decision variable z_{ijse}, which is expanded to z_{ijse}^{c} in the non-collaborative model. This is done because the non-collaborative model does not allow collaboration between the different companies. Therefore, it is necessary to ensure that trucks only carry freight from the same company. Adding the company information for each dispatched integer quantity of trucks is needed to prevent companies from working together. It should be mentioned that combining commodities from the same company is still possible. While the objective functions (E1) and (E8) are only expanded by the company index, constraint (E6) has a bigger difference from the collaborative model. As companies are not working together in the non-collaborative model, the quantities are only summed up over all commodities, but not all companies, as the constraint has to hold for each company individually. Even if commodities from different companies use the same arc in the same time period, with enough quantity left, the non-collaborative model uses one truck per company involved. Overall, the collaborative model is the non-collaborative model with fewer restrictions considering the dispatched integer quantity variable z_{ijse}, respectively z^c_{ijse}. The benefits of the more general collaborative model are analyzed in the next chapter.

4 Computational Study

The goal of this work is to analyze the potential cost reduction through collaborative service network design. This is tested on different settings, which are introduced in the section **"Problem Instances" (4.1)** and further explained in the section **"Experimental Design" (4.2)**. Section **4.3** covers the implementation of the models, followed by a detailed analysis of the results **(4.4)**. The chapter concludes with an approach to fair distribution of the additional profit gained through collaboration **(4.5)**.

4.1 Problem Instances

Based on the knowledge acquired by the sources above and the restrictions on run-time, the following properties are used for the centralized service network design model with collaborative planning:

General information

- Commodities (K): 20-80
- Planning horizon (T): 12 time periods (1hour intervals)
- Companies (C): 3,5 or 10 companies

Commodity information:

- Origin node of commodity (o_k)
- Destination node of commodity (d_k)
- Commodity size: 1-5 units (q_k)
- Corresponding company (c_k)
- Time commodity becomes available / earliest possible leaving time (e_k)
- Latest possible arrival time (l_k)

Network information:

- Terminals/Nodes (N): 10
- Arc density: Between 49 and 89%
- Truck capacity (u_{ij}): 5,10 or 20 units
- Travel time/distance between Nodes (v_{ij}): 2-4 time periods/ cost units
- Fixed costs per transfer (f_{ij}): 10, 20 or 40 cost units
- Additional costs for reloading (r): 0,1 or 5 cost units
- Time window between e_k and l_k: 2*v_{ij}, 1.5*v_{ij} or l_k= last time period

4.2 Experimental Design

The initial setup of a problem instance covers 40 commodities with ten nodes and twelve time periods. The fixed costs of a truck are 20 units, the costs for reloading are one, and the truck capacity is ten. Three companies have to plan their commodities on a network with an arc density between 49 and 76 % within time windows that are two times the minimum traveling time between the origin and destination. If there is no direct connection between the starting and ending nodes, the time window is enlarged. In this case, due to the short time horizon, the latest possible arrival time is set equal to the last time period, which is twelve for all problem instances. These properties are used to create five instances that are different from each other through the randomly assigned origin/destination pairs, the network with its density and distances, and the commodity company pairs. Moreover, the quantities of each commodity and the time a commodity becomes available are assigned randomly to each instance. This is performed to utilize the average outcomes from the five instances, providing more robust information compared to testing a single instance for each setting. Based on the five basic instances, five more instances are created each time one of the parameters is changed. This is done for a total of 18 different parameter settings, resulting in 90 instances that are tested for the collaborative and non-collaborative models.

One of those parameters that is changed, is the number of companies that are working together in the collaborative approach. Three, five, or ten companies are considered in the different problem instances. First, the service network design problem is solved for each company working individually. Then the problem is solved with a collaborative approach. The collaborative approach allows a company to combine shipments not only of their own company but of different companies. The idea behind this approach is to combine the resources of all companies, which should yield better results in terms of saving travel time and distance and, consequently, in terms of saving costs.

The ratio between the different cost parameters has a big influence on the results and, hence, on the comparison of the collaborative and non-collaborative models. Therefore, different costs and different ratios are tested with the combination of the following values: Reloading costs can take values of zero, one, or five, and the fixed costs are set to 10, 20, and 40. The travel time and distance costs stay within the same range of two to four time units. It should be mentioned that the costs per distance are further multiplied by the quantity carried from the corresponding nodes i to j. A reasonable value for the costs of reloading can be achieved by considering the additional time needed and the probability of having to use an additional time period. Consequently, one must consider the possibility that, due to this additional time period, the commodity does not reach its destination within the latest possible arrival time. In the problem setting of this thesis, a twelve-hour planning horizon with time intervals of 60 minutes is used. Assuming the reloading takes ten minutes, the chance of needing an additional time period is 1/6. If the commodity reaches its destination in time, the reloading process would not result in additional costs, but there is still the possibility that the commodity could not arrive in time due to the reloading if this additional time is not considered. Nevertheless, the reloading costs can be considered considerably low compared to the fixed costs of using a truck. Therefore, reloading costs are set to one. For the sensitivity analysis, a different reloading cost of zero and five is evaluated. In general, it can be said that due to the low costs of reloading compared to fixed and travel costs, the reloading process has a rather small influence on the solution. Taking Boland et al. (2019) as a reference, initial fixed costs of 20 seem to be a reasonable value considering the ratio to the average transportation time and costs of three and the initial reloading costs of one. Fixed costs of ten and 40 are tested to get a better sense of the influence of this parameter.

Further characteristics that are tested are the transported units per truck and node, which can either be five, ten, or 20. The number of commodities in the problem varies from 20 to 80. Problem characteristics that stay the same over all instances are the planning horizon (twelve time periods) and the number of nodes (10), which can be used as origin, destination, or intermediate terminals. The influences of different parameters are analyzed by changing only one parameter for multiple problem instances and comparing the results.

In the real world, it is unrealistic that a network is a complete graph where every node or terminal has a direct connection. Taking the railway network of Austria as an example, there is no direct connection from Vienna to Innsbruck without an intermediate stop. It would be more reasonable if the train went from Vienna to Salzburg and then from Salzburg to Innsbruck. In this example, the arc Vienna-Innsbruck does not exist, but reaching Innsbruck is possible by using the arc Vienna-Salzburg and Salzburg-Innsbruck. An arc density of around 50 to 80 % is assumed, which means that only 50 to 80 % of the total possible arcs between all nodes exist. When the network is created, each node connection is given a certain distance or number of time periods to traverse the arc. The possible values of time periods are two to four (feasible paths) and values bigger than twelve (infeasible or non-existing paths). The values of the arcs that are not possible are set to values bigger than twelve, because twelve is the total number of time periods. Consequently, these arcs will not be chosen by the model, and different paths have to be found to find a feasible solution.

Figure 11 shows a complete graph with ten nodes. This represents the easiest case for a network, where each node can be visited directly from each node without any need for an intermediate node. For this graph, all possible connections exist.

A probably more realistic representation of a network is shown in figure 12. This graph has an arc density of 51% which means that only about half of all possible arcs exist in this network. Additionally, the distances between each directly connected node are given. If there is no direct connection, another node is needed to reach the destination node. For example, going from node one to node two, an intermediate node to use could be node six. The number of connections at each node can be very different. This can be seen by comparing the connections between node four, which only has a

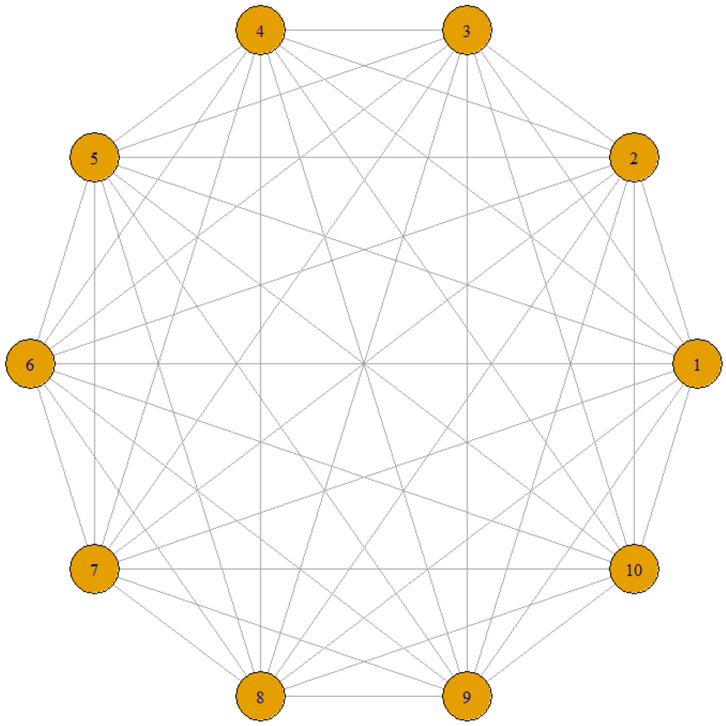

Figure 11: Complete graph with 10 nodes

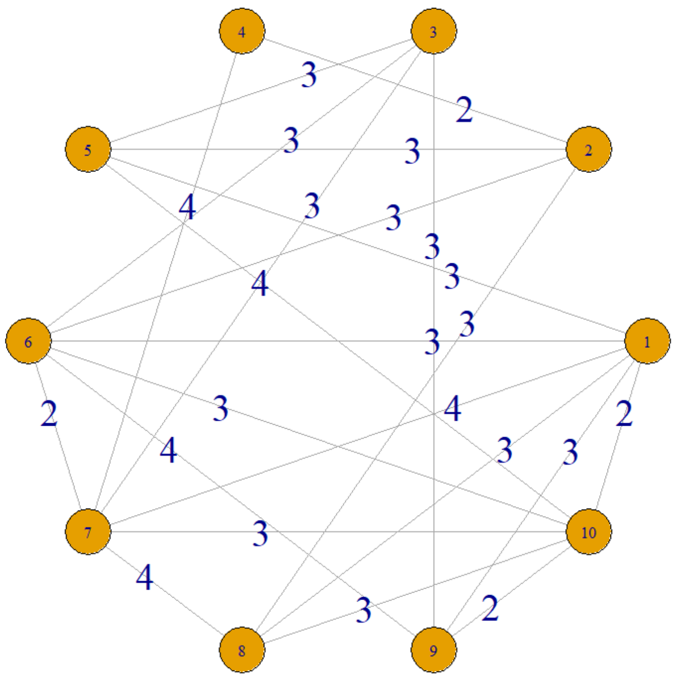

Figure 12: Graph solution example with 51% arc density and corresponding distances

direct connection to nodes two and seven, and node ten, which has a total of six direct connections. It should be noted that while the actual network appears different, a cyclic network is chosen here for simplicity of representation.

The calculation of the latest possible arrival time is based on the shortest travel time. The initial time buffer is equal to two times the shortest travel time between the origin and destination node. So, for example, if a commodity is available in time period three and has a minimum travel time of four time periods, the latest possible arrival time would be eleven (3+2*4). Other time windows that are tested are 150% of the travel time (3+1.5*4) and a more free setting, where the latest possible arrival time is set to twelve, which is equal to the last time period for all commodities.

Origin-destination pairs without a direct connection automatically have the latest time period as their latest possible arrival time. There is a good reason for that, as a minimum of two arcs is required, which takes more time, and with only twelve time periods, it makes sense to set the latest possible arrival time to the highest value, to ensure the problem remains feasible.

4.3 Implementation

All problem instances are generated with the **programming language R** and are then transferred to **FICO Xpress Mosel**, where each instance is run on the collaborative and non-collaborative models. The results of the model are then saved in an Excel file and further analyzed in the subsequent section.

4.3.1 R

Instance generation in R is rather straightforward and without any need for complex code. To ensure the instances can be reproduced, "set.seed" is used. Some parameters and set sizes have to be declared before creating the instances, as they influence the further parameters. Therefore, first of all, the number of commodities, nodes, time periods, and companies, as well as the maximum quantity of a commodity, are defined. Parameters like reloading costs, fixed costs, or truck capacity can still be modified in the.dat file used in Xpress Mosel. Each instance is saved in a separate.dat file, from where the data is read in from the model in Xpress Mosel.

Properties like the origin and destination of the commodity are different for each problem instance, as they are generated randomly with possible values between one and the total number of nodes. This holds for the randomly assigned company to which the commodity belongs. The possible values are equal to the total number of companies in the corresponding problem instance. Each commodity can start and end at each node, but it should not have its origin as its destination. An additional code line ensures that the origin and destination are different. The commodity size can take values from one to five units, with the same probability for each quantity. All properties in this paragraph can be produced by using the same principle of using the sample function. The length and possible values are set as described for every single parameter, and the argument replace=TRUE ensures that, for example, a node can be the origin for more than one commodity, as the node can still be chosen after it has already been selected for a different commodity. The earliest possible time a commodity can leave is restricted to values within the first third of the planning horizon. This is necessary because commodities starting in later time periods would have too little time to be dealt with within the same planning horizon. Due to the travel time, which can cover a significant part of the total planning horizon, and the additional time, which is needed for planning flexibility, commodities that are not available within the first third of the planning horizon are unlikely to reach their destination within the same planning horizon. In a real-world problem, such commodities would normally be planned for the next planning horizon, but in this thesis, only one planning horizon is considered.

The arc density is created by using probability values for feasible and infeasible distances. Therefore, the arc density is not a fixed value and varies in a certain range of about 49 to 76% for the normal setting and between 82 and 89% for the instances especially tested on higher arc density. The so-called infeasible distances are all values above twelve, which is the total number of time periods and therefore infeasible due to other constraints. This means node pairs with an infeasible distance cannot be used directly and have to find a path over an intermediate node. For this problem, it is assumed that traveling from node i to j takes as long as traveling from node j to i. Therefore, an additional code line is used to ensure the symmetry of the distance matrix. The latest possible arrival time is created as described earlier in the previous subsection. Dependent on the current setting, l_k is equal to 2*v_{ij}, 1.5*v_{ij} or the last possible time period, which is twelve for all instances. If one of the first two settings creates a value bigger than twelve for l_k, the latest possible arrival time is set to twelve. At the end, all relevant data is printed to the console and then transferred to the .dat files, which are needed for running the data in Xpress Mosel.

4.3.2 Xpress Mosel

The implementation part of Xpress Mosel is the translation of the mathematical model defined in subsection 3.2 into Xpress Modesl code. All sets and parameters need to be declared, including information about their size and type (integer, real, or range). This also has to be done for the decision variables. After reading the corresponding data file, it is important to restrict the decision variables as much as possible. The two different types of decision variables (x^{ck}_{ijse} and z_{ijse} for the collaborative and z^{c}_{ijse} for the non-collaborative model) have a lot of possible combinations. Many of these combinations are 0 anyway and can therefore be set to 0 before running the model. Consequently, fewer decision variables have to be considered in the model, which makes it more efficient and can save a lot of run time, especially for bigger problems. The restrictions used for the decision variables of the collaborative and non-collaborative models are of four different types. As the minimum traveling distance covers two time periods and only twelve time periods are considered, the latest possible start from any node can be in time period ten. Therefore, the starting time s is restricted to s<11. For the arrival time in node j, only one time period should be possible. This is the time period equal to the starting time from node i and the traveling time going from node i to j. All decision variables with a different arrival time e are set automatically to 0 with the restriction e=s+v_{ij}. This is a huge restriction, creating significantly fewer decision-making variables. The third restriction is the condition that only commodity company pairs that exist are created. This means that for every commodity, only a decision variable is created with the combination of the corresponding company by setting c=$c_k(k)$. Commodities are transported through a network that is not complete. For some node combinations, there is no direct connection, and it is necessary to use other nodes as intermediate stops to get to the desired node. For this thesis, all node combinations that have no direct connection have a traveling distance that is longer than the planning horizon of twelve time periods. Consequently, all decision variables, including a node combination with a longer travel distance than twelve, are not considered for the rest of the problem and set to 0.

The problem formulation is, in most parts, identical to the formulation of the mathematical model in subsection 3.2. The objective function (1) is summed up over the three different cost terms: fixed, variable, and reloading costs. Constraint (2) is implemented with if and else conditions to deal with the different cases of origin, intermediate and destination nodes. The in-going arcs from node j are subtracted from the outgoing arcs. Whether j is an origin, intermediate, or destination node of the corresponding commodity, the result of the difference between outgoing and in-going arcs should be 1 (origin), -1 (destination), or 0 (intermediate), respectively. The most time-consuming constraint of the model is constraint (3), which ensures that a commodity can only leave an intermediate node at a time point bigger or equal to the arrival time at this node. There are quite a lot of combinations to be checked, as the condition has to run over a for-all loop considering all possible combinations left, with the companies c, commodities k, nodes i, j, and h, and time periods s1 and e2. Conditions for this constraint are that e1 (arrival time at the intermediate node) needs to be smaller or equal to s2 (starting time from the intermediate node). Also, holding-arcs do not have to be considered for this constraint, as this only affects arcs that leave the intermediate node. Constraint (4), which sets all variables to 0 if the commodity company pair does not exist or if the travel time does not meet the equation s=e+v_{ij}, was not necessary to implement, as these variables have already been excluded (set to 0) from the model when creating the decision variables, as already mentioned earlier. Possible positive decision variable values are further restricted by constraint (5), which makes sure that the starting time is bigger or equal to e_k (the earliest possible time commodity k can leave) and the arrival time is smaller or equal to l_k (the latest possible time commodity k has to be at the destination).Constraint (6) covers the consolidation of commodities, if they are dispatched from the same node in the same time period. Binary values for all decision variables of type x_{ijse}^{ck} are enforced by constraint (7). For the last constraint (8), the decision variable types z_{ijse} for the collaborative model and z_{ijse}^{c} for the non-collaborative model have to be positive and integer.

The implementation of the non-collaborative model is almost similar to the one in the collaborative model. The only difference is the expanded version of z_{ijse}^{c}, which now uses the company information of the commodity. All parts of the model, including the decision variable type z (objective function

(1) and constraints (6) and (8)), are simply upgraded by the company information.

At the end of the models, all relevant results are printed on the console. These are then further transferred to an Excel file, where all the results are saved in one table. Data printed to the console includes the model that has been used (collaborative or non-collaborative), the problem instance that has been used, the total costs of the model (objective value), and the particular fixed, variable, and reloading costs, as well as the number of reloadings, trucks, and total arcs used. At the end, the arc density of the current network of the problem instance and the costs for each company are printed on the console. As the decision variable z_{ijse} only carries the company information for the non-collaborative model, these values only make sense for the non-collaborative model, while those for the collaborative model are more difficult to interpret. This is because the decision variables of type Z in the collaborative model do not tell us to which company the truck belongs or if the truck carries commodities from different companies. In this case, it would be even more difficult to assign the correct costs for this truck to the different companies. During the programming process, the positive decision variables have been printed to the console. This was necessary for monitoring the correctness of the problem and understanding possible difficulties.

It should be mentioned that only the expenditure of restricting the number of decision variables as much as possible enabled the model to solve instances with more commodities. A lot of decision variables are not created, such as commodity-company pairs that do not exist, node pairs with a different distance than the actual transportation time, and decision variables with a too-late starting time considering the required transportation time. Due to these restrictions, it was possible to increase the maximum number of commodities that can be solved in the model from 20 to 80. This important step gives us a better understanding of the actual possibilities of collaboration with more commodities involved.
After running the instances, the results can now be analyzed. The most interesting results are taken from the Excel file and visualized with the programming language R. The different graphs are created with the packages **ggplot** for bar charts and **igraph** for graphical representations of the network.

4.4 Results

The results of the 90 problem instances that have been run for the collaborative as well as the non-collaborative model are now analyzed. The different parameter settings that have been used can be seen in table 1. For each setting, five problem instances have been generated and tested. Those settings include variations in the number of commodities or companies, as well as different cost ratios. Additionally, the arc density, the truck capacity, and the length of the time windows have been varied.

Setting	# Commodities	r	f_{ij}	u_{ij}	# Companies	Time window	Arc density
Basic Setting	40	1	20	10	3	$2 \cdot v_{ij}$	49-76 %
20 Commodities	**20**	1	20	10	3	$2 \cdot v_{ij}$	49-76 %
30 Commodities	**30**	1	20	10	3	$2 \cdot v_{ij}$	49-76 %
50 Commodities	**50**	1	20	10	3	$2 \cdot v_{ij}$	49-76 %
60 Commodities	**60**	1	20	10	3	$2 \cdot v_{ij}$	49-76 %
70 Commodities	**70**	1	20	10	3	$2 \cdot v_{ij}$	49-76 %
80 Commodities	**80**	1	20	10	3	$2 \cdot v_{ij}$	49-76 %
5 Companies	40	1	20	10	**5**	$2 \cdot v_{ij}$	49-76 %
10 Companies	40	1	20	10	**10**	$2 \cdot v_{ij}$	49-76 %
Arc density 82-89%	40	1	20	10	3	$2 \cdot v_{ij}$	**82-89%**
Truck capacity 5	40	1	20	**5**	3	$2 \cdot v_{ij}$	49-76 %
Truck capacity 20	40	1	20	**20**	3	$2 \cdot v_{ij}$	49-76 %
Fixed costs 10	40	1	**10**	10	3	$2 \cdot v_{ij}$	49-76 %
Fixed costs 40	40	1	**40**	10	3	$2 \cdot v_{ij}$	49-76 %
Reloading costs 0	40	**0**	20	10	3	$2 \cdot v_{ij}$	49-76 %
Reloading costs 5	40	**5**	20	10	3	$2 \cdot v_{ij}$	49-76 %
Time window 1.5*v_{ij}	40	1	20	10	3	$1.5 \cdot v_{ij}$	49-76 %
Time window l_k=12	40	1	20	10	3	l_k=12	49-76 %

Table 1: Problem instance settings

4.4.1 Overall Results

Part of objective function	**Cost development over all instances**
Variable Transportation Costs	1.1%
Reloading Costs	98.01%
Fixed Costs	-25.11%
Total Costs	**-14.02%**

Table 2: Overall results from non-collaborative to collaborative

Considering the results of all test instances in table 2 it can be said that costs are saved by the reduction of trucks that had to be used, while there was only a slight increase in total transportation distance. Over all instances, the increase in the variable part of the transportation costs is 1.10%. More consolidation possibilities lead to more reloading. Consequently, reloading costs increase by an average of 98.01% per instance. Although two parts of the objective function are more expensive in the collaborative model, there is still a significant cost reduction compared to the non-collaborative model due to the big impact of the fixed costs of using a truck. The average saved fixed costs are 25.11%. All cost functions combined result in a total average cost reduction of 14.02% for the collaborative model.

Table 3 introduces the highest and lowest changes going from the non-collaborative to the collaborative approach. The following results show the average values over the five instances of a certain parameter setting. As a point of reference, the results of the basic instances are provided in the last

Instance Setting	Characteristic	Corresponding Inst.	Basic Inst.
10 Companies	Highest Total Cost Improvement	22.51%	12.75%
Truck capacity 5	Lowest Total Cost Improvement	5.46%	12.75%
10 Companies	Highest # Reloading Increase	381.75%	72.08%
80 Commodities	Lowest # Reloading Increase	44.80%	72.08%
10 Companies	Highest Fixed Cost Improvement	37.82%	23.21%
Truck capacity 5	Lowest Fixed Cost Improvement	9.54%	23.21%

Table 3: Results summary - extreme values

column. The highest cost improvement (22.51%), the highest increase in the number of reloadings (381.75%) and the highest fixed cost improvement (37.82%) all have been reached in the instances with ten companies involved. This clearly shows the improved benefit when more companies are involved. The lowest changes in total cost improvement and fixed cost improvement have been achieved by the test instances with a truck capacity of only five units. This parameter setting makes it more difficult to consolidate the shipments of commodities, achieving a total cost improvement of 5.46% and a fixed cost improvement of 9.54%. The commodity size is distributed uniformly between one and five units. Consequently, consolidating only two commodities, which is feasible for all combinations of commodities with trucks having a capacity of ten units, is now infeasible for a significant portion of pair combinations. Therefore, in this setting, the advantage of the collaborative approach is restricted. Because the collaborative approach offers more consolidation options, there should be a lot more reloads. As already mentioned, the biggest increase in this variable happens when using the setting with ten companies. The lowest change (44.80%) to the non-collaborative model happens for the test instances with 80 commodities. A reason for this is that the non-collaborative model also takes advantage of having more commodities per company, as each company has more possibilities for combining shipments of their own.

Figure 13 shows a graphical representation of the transportation routes in the optimal solution of instance **"BasisMD1"** with 40 involved commodities. The directed arcs show the transportation of a commodity from node i to j. Each color represents a corresponding company. Arcs that go from the same node i to the same node j are not necessarily transported together, but this is possible. To make sure if commodities are transported together, the information for the corresponding time periods would be needed, which is not depicted in the graph. Anyway, important nodes can be identified. For example, it can be seen that a lot of arcs arrive at and leave from node ten, which seems to be an important intermediate stop. The fact that carriers do not have their own nodes is another crucial point to make. Each node can be an origin or a destination for each company.

The run-time for solving the collaborative model is extremely problem-dependent, as can be seen in table 4. For three different problem settings, the minimum and maximum run-time out of the corresponding five problem instances are summarized in this table. It took between seven and 39 seconds for the model to solve instances of the setting with 40 commodities. Using 50 commodities, the min-

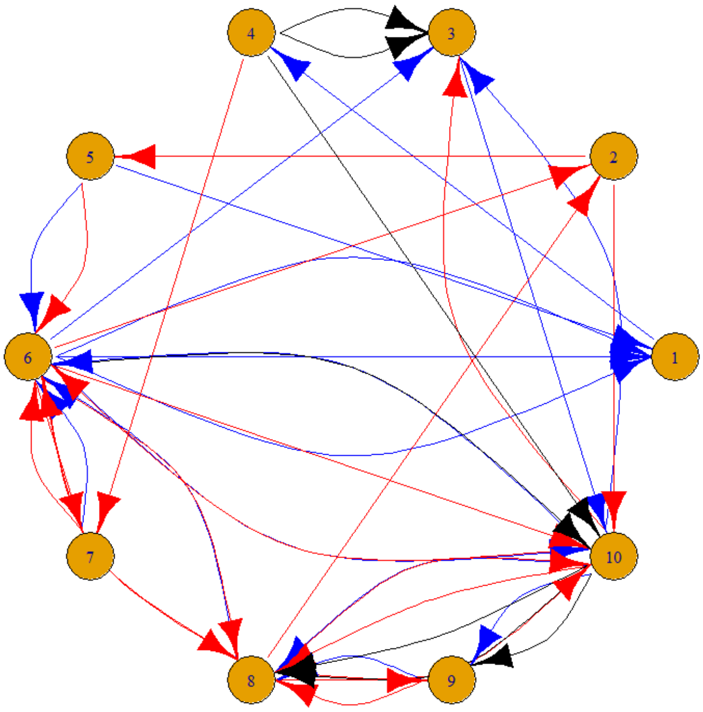

Figure 13: Graph solution example representing all selected services

Instance Setting	Min	Max
Basic Instances (40 Comm.)	7 sec	39 sec
50 Commodities	14 sec	2:00 min
Time window l_k=12	3:05 min	> 1 hour

Table 4: Runtime of the collaborative model

imum and maximum run-times are already increased to 14 seconds and two minutes, respectively. It takes the model even longer to find the proven optimal solutions for a more free setting, like the instances with all the latest possible arrival times being set to the latest possible time period of twelve. For this setting, the minimum run-time was 3:05 minutes, and for two out of the five instances, the run-time was longer than an hour. It should be mentioned that the run-time only considers the time to solve the model but not to create and load the model, which takes some time depending on the size of the model.

# Commodities	Time for creating model	Opt. Solution found	Average Gap to Opt. Sol.
40	2 Minutes 30 Seconds	5/5	0%
50	4 Minutes	5/5	0%
60	7 Minutes	3/5	0.28%
70	9 Minutes	1/5	0.66%
80	12 Minutes	1/5	1.26%

Table 5: Test instances with more commodities

Time for creating the model and further difficulties of testing with more commodities are presented in table 5. While it only takes an average of two minutes and 30 seconds to set up the model for 40 commodities across the five instances, this value quickly increases with more commodities involved. This rapid increase to four, seven, nine, and twelve minutes with each additional ten commodities explains why it is not possible to test larger instances. At 90 commodities, it is no longer possible to set up a model before the program runs out of memory. Not only the model set-up time, but the model run time increases with more commodities. The maximum runtime is set to one hour. If the optimal solution is not found within one hour, the best solution found up to that point is accepted. Due to the increased runtime, for 60 or more commodities not all instances could be solved to proven optimality. This explains the average gap between the found solutions and the lower bounds for the solutions after one hour of runtime. For 80 commodities the current solution found with a one-hour runtime could be further improved by up to 1.26%. Nevertheless, it is possible that all solutions found up to this point are already the optimal solutions for the corresponding problem instance. The mentioned run times up to now have all referred to the collaborative model. Since the non-collaborative model has more constraints considering that commodities can only be shipped by trucks of the same company, the optimal solutions are found much faster. In the non-collaborative model, the optimal solutions are found on average in 23 seconds for the instances with 60 commodities and in 37 seconds for the instances with 70 commodities. The time to create the non-collaborative model is pretty similar to that for the collaborative model.

4.4.2 Influence of different parameters on overall cost improvement

As shown in figure 14, the cost improvement also depends on the size of the problem and, respectively, the total number of commodities transported. The two different colors are only used for better recognition and do not have any further meaning. While the differences for 20, 30, and 40 instances are rather small, a significant improvement can be seen for the instances with 50 commodities. The biggest average cost improvement over the five instances has been found for the setting with 70 commodities involved, with an improvement of 17.49%. The slightly smaller improvement for the instances with 80 commodities can be explained by the rather small number of instances per setting. It can be expected that more instances per setting would lead to a higher improvement for the 80 commodity instances compared to the 70 commodity instances. The flattening increase in cost improvement for instances with over 50 commodities suggests that the potential for collaboration has already been well exploited. This means that while a significantly larger number of commodities may yield an higher improvement, it should not be much higher than what we see here for 60, 70, and 80 commodities.

Figure 15 shows the average costs of the non-collaborative model (orange) and collaborative model (green) based on the number of companies available in the corresponding test instance. A higher number of companies has a higher advantage for the collaborative model. For the collaborative model,

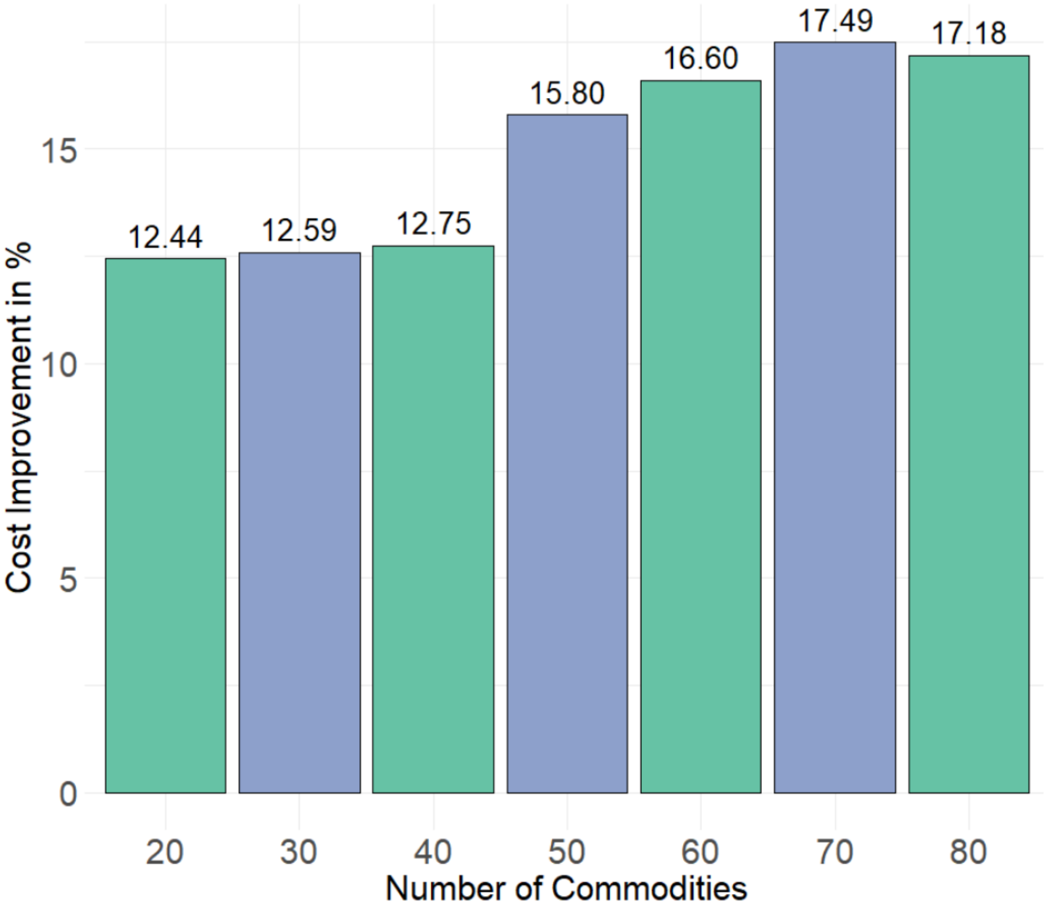

Figure 14: Cost improvement for varying number of commodities

there is no difference if three, five, or ten companies are involved, because the company does not matter here and all commodities can be consolidated with others. In this case, the cost differences in the green bars are random. For the non-collaborative model, this is different, as consolidation is only possible for commodities that belong to the same company. More involved companies results in fewer consolidation possibilities because the total number of commodities stays the same, and therefore, instances with more companies have fewer commodities per company. This means that more involved companies normally result in higher costs in the non-collaborative model.

Figure 16 shows the cost improvement of the collaborative model considering different reloading costs. The results show that with higher reloading costs, the advantage of the collaborative model is getting smaller compared to the non-collaborative approach. This can be explained, as the number of reloadings is considerably higher in the collaborative model, and therefore higher reloading costs have a bigger effect than in the non-collaborative model. Taking the fixed costs and the variable transportation costs into account, a reloading cost of one seems to be the most reasonable value, as explained earlier in the section **"Experimental Design"**".

Figure 17 shows the average cost improvement on various parameter settings of fixed costs, with all

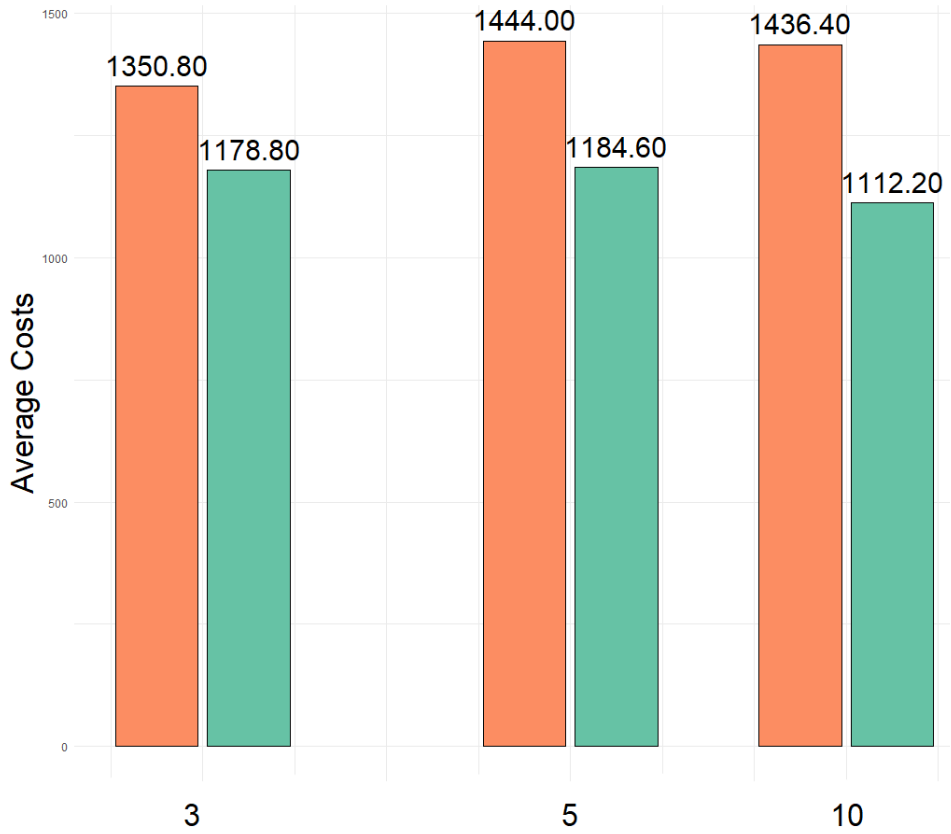

Figure 15: Cost improvement for varying number of companies
Orange: Non-Collaborative, Green: Collaborative

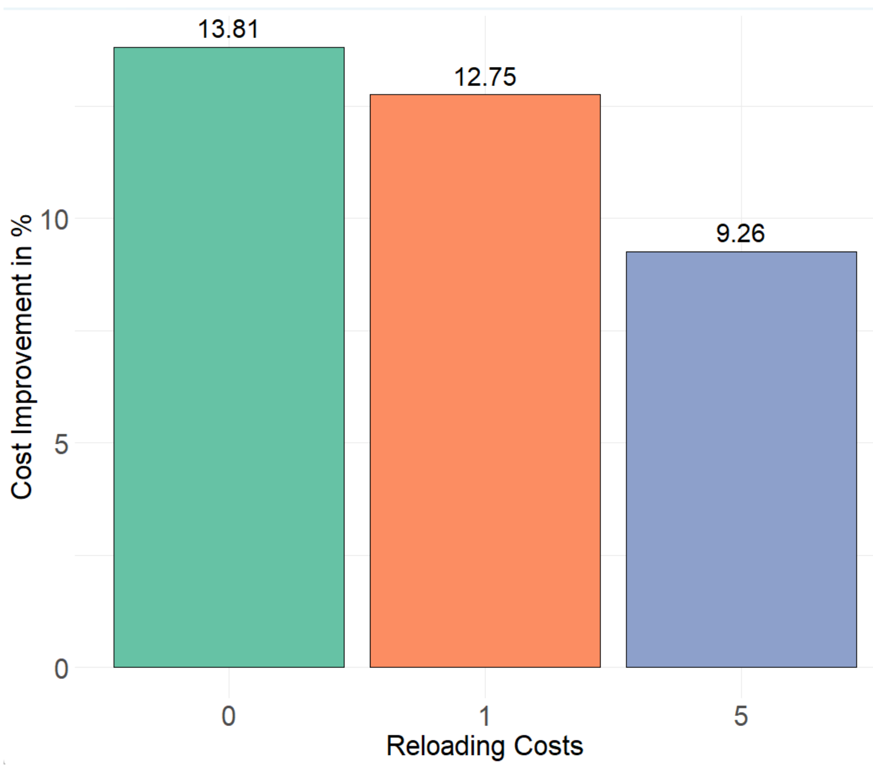

Figure 16: Cost improvement for varying reloading costs

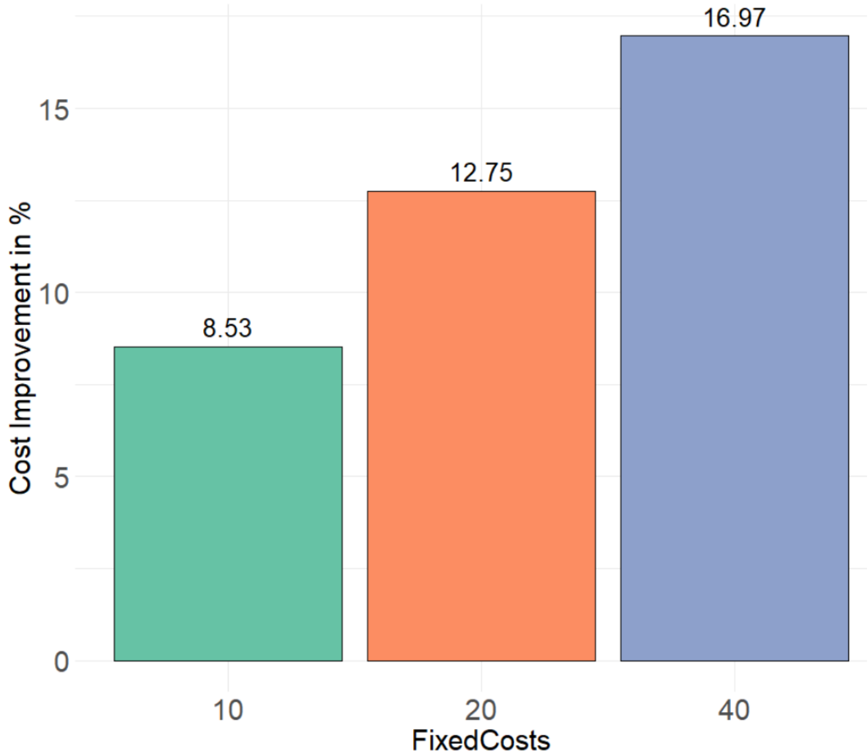

Figure 17: Cost improvement for varying fixed costs

other parameters staying the same. Higher fixed costs are a bigger advantage for the collaborative model compared to the non-collaborative approach. This makes sense because cutting back on the number of trucks used is even more crucial in light of rising fixed costs. Due to more consolidation possibilities, it is easier for the collaborative model to minimize the number of trucks.

One setting that has been tested without yielding significant differences is the arc density. As comparing single instances does not make much sense, the average value of the five instances with lower arc density (49% - 76%) is compared with those five instances with higher arc density (82% - 89%). In fact, the cost improvement through the collaborative approach is 12.75% for low arc density and 12.41% for high arc density. With this small number of instances and small difference, it cannot be said whether higher arc density would speak for higher or lower savings using the collaborative model. Higher arc density gives more transportation possibilities, which has a positive effect on both the collaborative and non-collaborative models. This can be seen by comparing the average objective values of the collaborative and non-collaborative models. While for the instances with lower arc density, the average total costs in the non-collaborative model are 1351, these costs are only 1191 for the instances with higher arc density. The collaborative model has similar cost differences, with lower total costs for the instances with higher arc density.

Figure 18 shows the influence of the truck capacity. More truck capacity yields more consolidation possibilities. Especially the low truck capacity of five units takes away the advantage of the collaborative model. As already mentioned earlier, the instances with a truck capacity of five units have

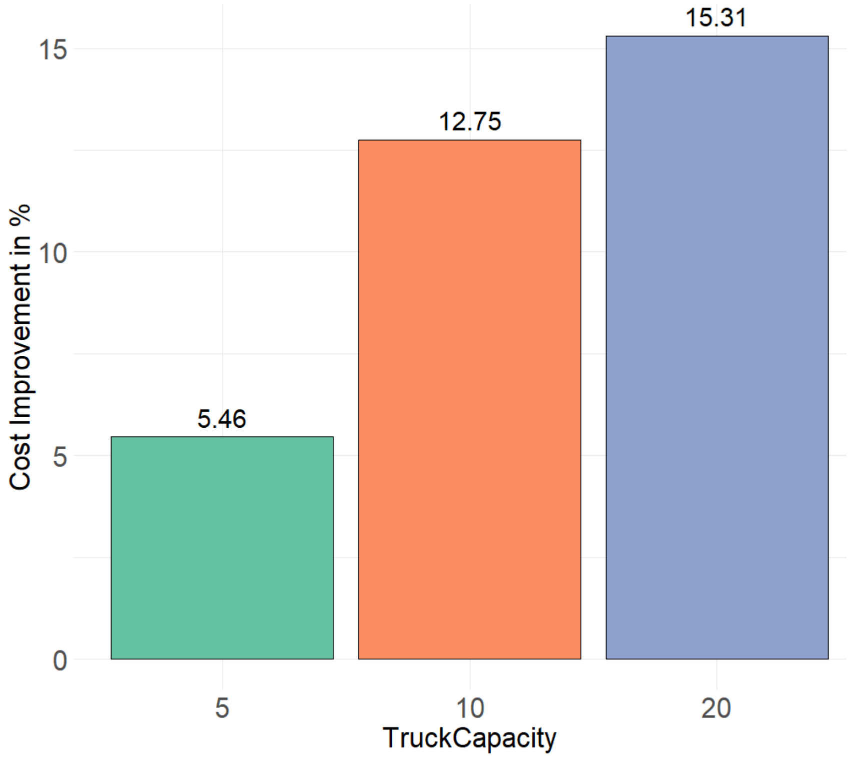

Figure 18: Cost improvement for varying truck capacity

the lowest average cost improvement of all the different settings that have been tested, because the consolidation possibilities are very limited.

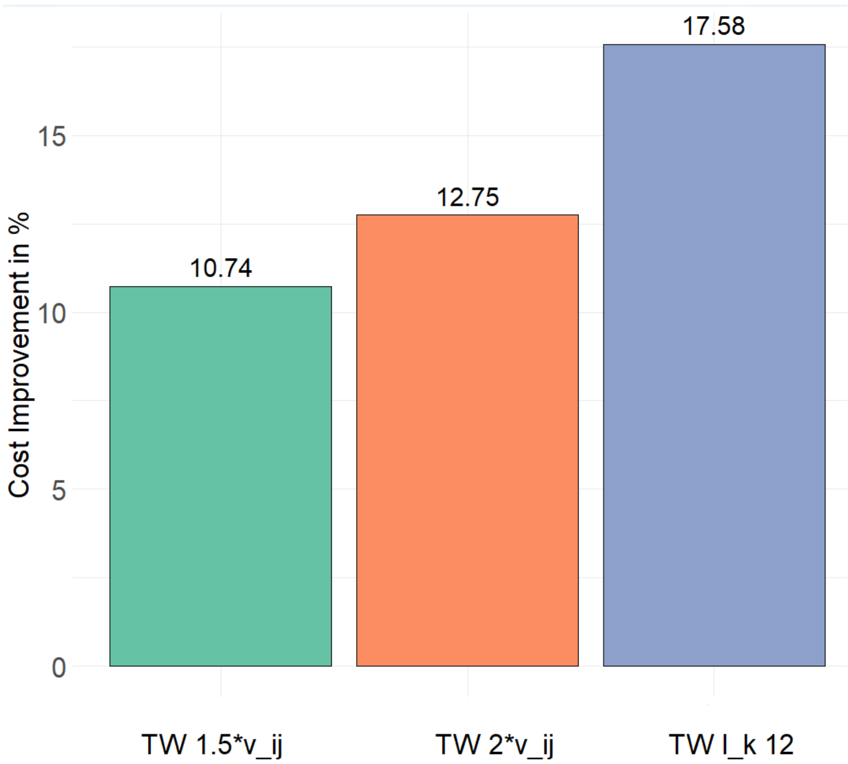

Figure 19: Cost improvement for varying time window ranges

The rising advantage of the collaborative model of instances with bigger time windows can be seen in figure 19. Similar to the previous results of higher truck capacity, bigger time windows give even more consolidation possibilities for the collaborative model and therefore yield higher cost improvements.

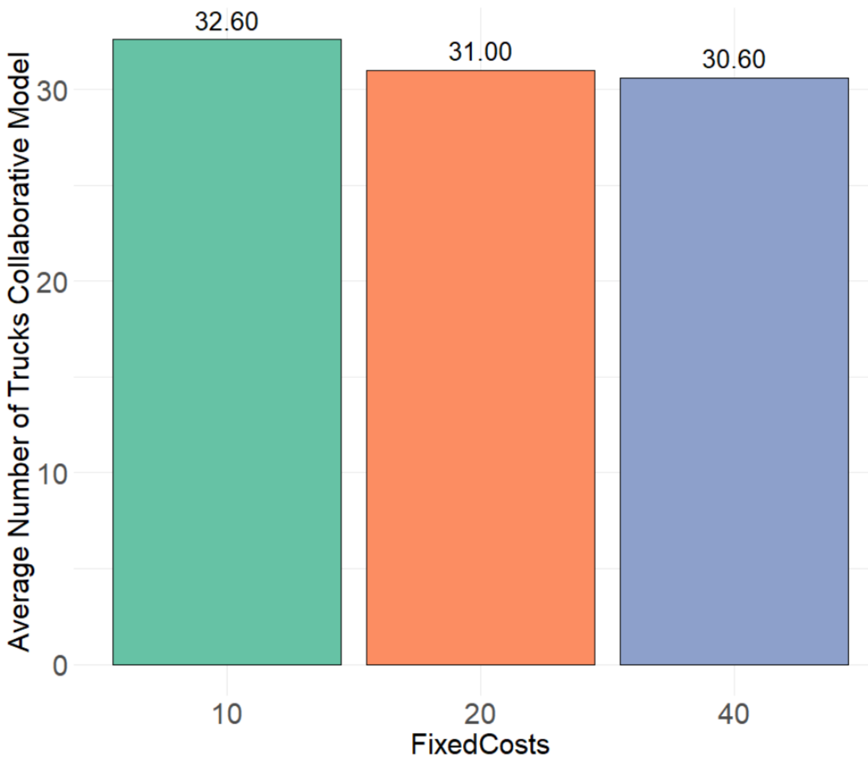

Figure 20: Number of trucks with changing fixed costs

4.4.3 Influence of different parameters on used number of trucks/reloadings

Figure 20 shows the average number of trucks in the collaborative model for various fixed costs. Although fewer trucks are used when fixed costs are higher, the difference is not very big. Fixed costs make up the majority of the objective function even at the lowest fixed cost option. This means that minimizing the number of trucks used is already a big issue for the low fixed costs option. From this, it follows that the number of trucks cannot be further decreased by a large value for higher fixed costs.

Similar to the various fixed costs, different reloading costs do not have a big influence on the average number of trucks used, as can be seen in figure 21. The slight increase in trucks for higher reloading costs can be explained as higher reloading costs follow fewer reloadings and consequently a higher need for trucks.

In Figure 22, the total number of reloadings is shown with different values of the fixed costs for the collaborative model. Higher fixed costs force the companies even more to use as few trucks as possi-

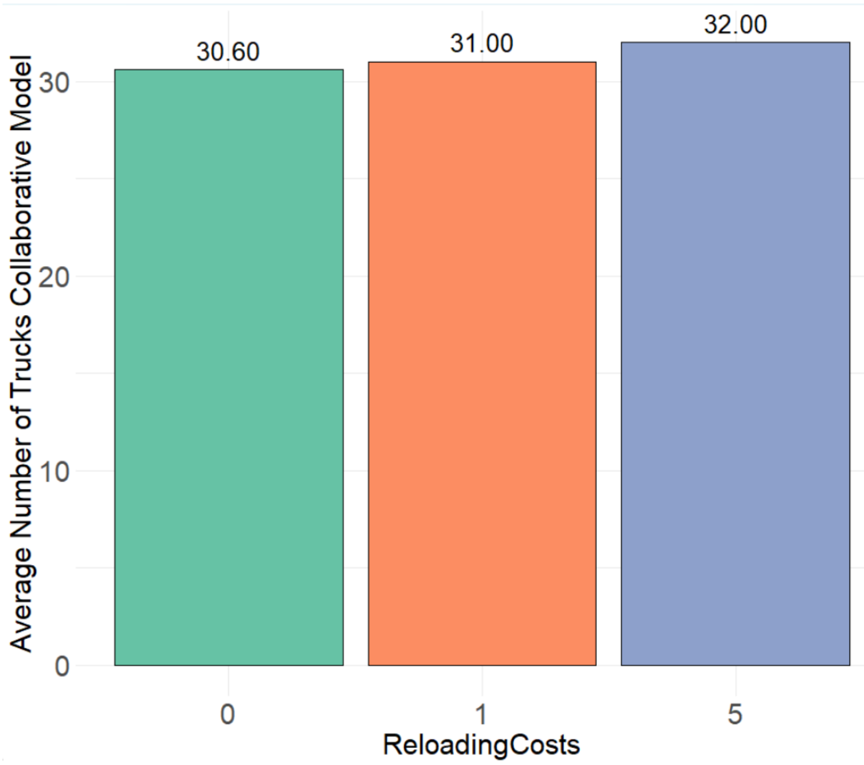

Figure 21: Number of trucks with changing reloading costs

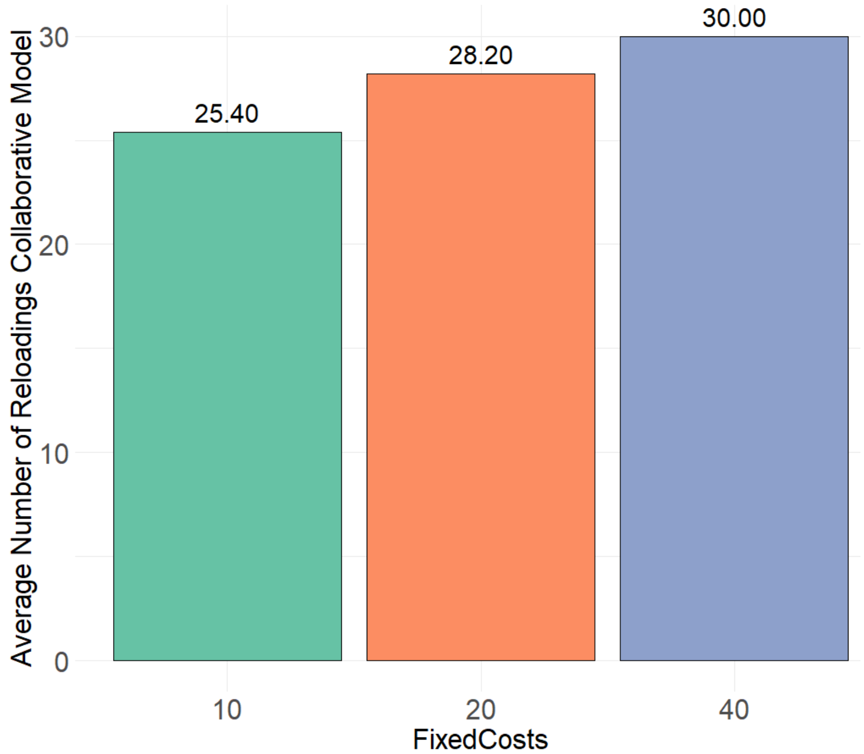

Figure 22: Number of reloadings with changing fixed costs

ble and therefore find as many consolidation possibilities as possible. It should be mentioned that the variable or transportation costs stay the same for all instances.

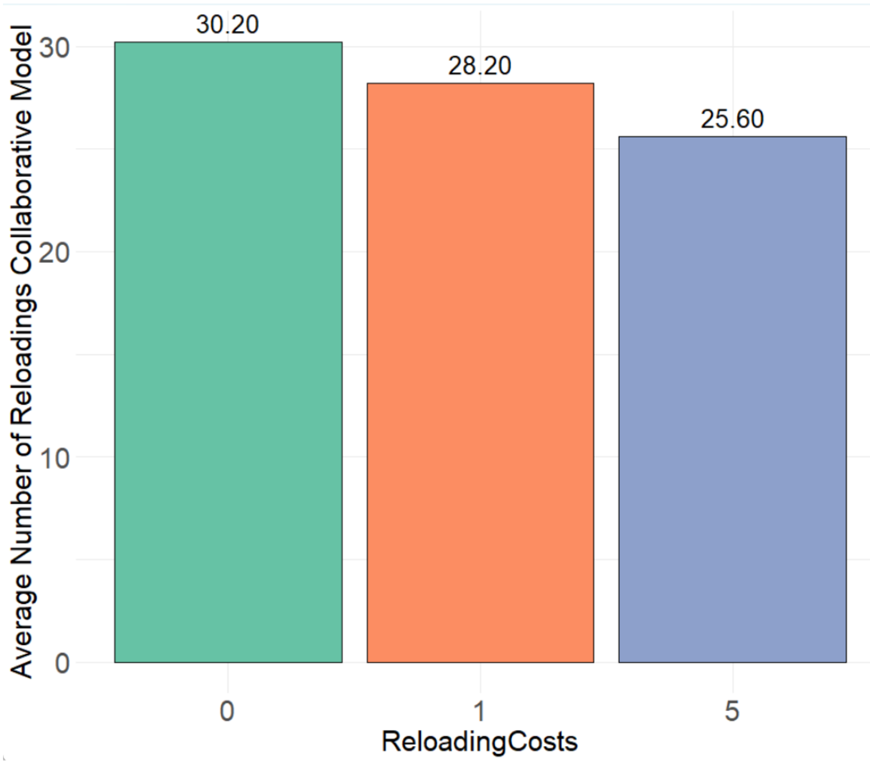

Figure 23: Number of reloadings with changing reloading costs

The relation between the reloading costs and the average number of reloadings is shown in figure 23. The differences here are bigger than for the average number of trucks. Additionally, the effect is the other way around, which means that higher reloading costs speak for a smaller number of reloadings.

4.5 Profit distribution

The results show that there is a significant cost reduction from implementing the collaborative approach. The objective function reduces the overall costs of all companies combined and therefore only yields a combined profit, which needs to be allocated between the different companies. This can be done in many different ways, as discussed in Cruijssen et al. (2010). A fair proportional distribution could, for example, be based on one of the following rules:

- Total load shipped
- Number of orders
- Transportation costs before the cooperation

Each of these rules has its own justification and can be executed with the available information. The challenge is now to find the most suitable or fairest approach considering this specific problem. In order to compare the three rules from above, the first test instance, **"BasisMD1"**, with 40 commodities is used. The results of the different rules can be seen in table 6.

For instance, in **"BasisMD1"**, the total load shipped by each company and the corresponding proportion of the total load of all companies are 31 (27.68%) for company 1, 42 (37.5%) for company 2, and 39 (34.82%) for company 3. The total profit gained by the collaborative model (total costs of 1218) compared to the non-collaborative model (total costs of 175) is 167. This would then result in a profit distribution of 27.68% * 167 = 46.23 for company 1, 37.5% * 167 = 62.63 for company 2, and 34.82% * 167 = 58.15 for company 3.

The total number of orders for each company in instance **"BasisMD1"** is 11 (27.5%) for company 1, 13 (32.5%) for company 2, and 16 (40%) for company 3. Following the rule of proportional number of orders, the profit distribution per company is 45.93 for company 1, 54.28 for company 2, and 66.8 for company 3.

The costs of each company for the non-collaborative approach can easily be calculated by the program. For the collaborative model, the decision variable type z_{ijse} misses the information about which company owns the truck. Additionally, it is possible that the commodities of more than one company are shipped together on the same truck. This further complicates a clear definition of how much cost arises for which company in the collaborative model. The third approach takes the relative costs of the non-collaborative model and allocates the profit gained based on those costs. Taking again problem instance **"BasisMD1"** as a reference, the total costs for each company are 410 (29.82%) for company 1, 441 (32.07 %) for company 2, and 524 (38.11%) for company 3. This would then result in a profit distribution of 29.82% * 167 = 49.8 for company 1, 32.07% * 167 = 53.56 for company 2, and 38.11% * 167 = 63.64 for company 3.

Rule	**Company 1**	**Company 2**	**Company 3**
Total load shipped	46.23	**62.63**	58.15
Number of orders	45.93	44.28	**66.8**
Costs before cooperation	49.80	53.56	**63.64**

Table 6: Profit distribution

Comparing the three rules, it can be seen that the outcomes are quite different. For example, company two would get the biggest profit when taking the total load shipped as a reference, but only the second highest profit considering costs before cooperation, and even the least if the number of orders is the chosen rule. This suggests the idea that no matter what rule is chosen, the true contribution of at least one of the companies is undervalued. Nevertheless, for this problem and with the known information, taking the costs before the cooperation as a guideline seems to be the fairest approach. In this case, the company with the highest costs but also the highest contribution gets the highest profit return. Every company saves the same percentage compared to the costs of the non-collaborative approach used before.

It should be mentioned that the results of one test instance should not be given too much weight, but also that comparing the test instances with each other is rather difficult. A fair distribution where every company is satisfied with the profit gained is very difficult to achieve. An advanced approach would be to combine the three rules that have been mentioned before and give them a proportional weight. The first approach would be to give each rule the same weight. For the instance **"BasisMD1"** this results in a profit distribution of 47.32 units for company 1, 53.49 for company 2, and 62.86 for company 3. Considering that the rules of total load shipped and number of orders are quite similar and the rule taking the costs before the cooperation into account seems to be the fairest one, the following weights are proposed. While costs before the cooperation contribute 60% to the total assigned profit, the other two rules (total load shipped and number of orders) contribute 20% each. These values are chosen rather randomly, based on intuition, as true fairness is not measurable with the available information. Using the weighted influence of the three different rules on instance **"BasisMD1"** from before, the profit distribution is as follows: Company 1: 48.31; Company 2: 53.52; and Company 3: 63.17. Compared to the arithmetic mean over the three rules, the differences in profit distribution are rather small. Independent of whether this is a fair distribution or not, the weighted consideration of all three rules should at least give a more fair solution than choosing only one of the rules.

5 Conclusion

Collaboration in service network design has enormous potential, as demonstrated by the analysis of all 90 instances that have been tested with the collaborative and non-collaborative models. More reloading possibilities in the collaborative model help to combine more shipments and therefore decrease the need for trucks or other transportation services. As the saved fixed costs for transportation services are the biggest part of the objective function, there is a large reduction in total costs. For some commodities, it might be even more beneficial to consider a small detour in the transportation route. The reason for using longer routes is that fewer trucks could be needed using alternatives to the shortest path, and total costs decrease, although the transportation distance increases.

The assumption established at the beginning of this thesis is supported by the results, which demonstrated a significant cost improvement for the collaborative model. The cost reduction in comparison to the non-collaborative model ranges from 5.5% to 22.5%, depending on the parameter values. The quantity of commodities included has a large positive impact on cost improvement, making it the most influential parameter. Due to restrictions on the memory of the program, 80 commodities are the maximum number to deal with. While the cost reduction for those instances was on average 17.2%, an even higher advantage of the collaborative model can be expected for instances with more commodities. Other important parameters that yield significant changes in the objective function are the number of companies involved, the range of the time windows, and the available truck capacity. The results of the test instances show that more companies, wider time windows, and higher truck capacity all lead to higher cost improvements in the collaborative model.

Exploring scenarios featuring an increased number of commodities and instances within each setting may provide valuable insights into the true impact and potential of this approach. While five instances per setting gives a reasonable approximation, more instances could yield more reliable results. Testing with a larger number of commodities would be possible by using more potent computers. Companies should be motivated by this work to realize that working together can only be advantageous financially. The way the problem has been created, in the worst case, a company has the same costs as before, but not higher costs. Therefore, each company that transports commodities from one location to another should be encouraged to consider collaboration with other companies. One unresolved question pertinent to implementing this approach in the real world involves determining how profits would be distributed among the companies. While various proposals are discussed in this thesis, reaching an agreement between cooperations might be seen as a more difficult path.

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