universität wien

MASTERARBEIT

Titel der Masterarbeit

„The Collaborative Carrier Routing Problem“

Verfasst von

Daniel Kaml Bakk.rer.soc.oec.

angestrebter akademischer Grad

Master of Science (MSc)

Wien, 2014

Studienkennzahl lt. Studienblatt:	A 066 914
Studienrichtung lt. Studienblatt:	Masterstudium Internationale Betriebswirtschaft
Betreuer:	O.Univ.Prof. Dipl.-Ing. Dr. Richard F. Hartl

Eidesstattliche Erklärung

Hiermit erkläre ich eidesstattlich, die vorliegende Arbeit selbstständig, ohne Benutzung anderer als der angegebenen Quellen und Hilfsmittel, verfasst zu haben. Die aus fremden Quellen übernommenen, direkten oder indirekt Gedanken, Konzepte und Zitate sind als solche kenntlich gemacht.

Die Arbeit wurde bisher weder in gleicher oder ähnlicher Form verfasst, noch einer anderen Prüfungsbehörde vorgelegt.

Wien, März 2014

Daniel Kaml

Danksagung

Ich bedanke mich sehr herzlich bei meiner Betreuerin Frau Dr. Margaretha Gansterer vom Lehrstuhl Produktion und Logistik an der Universität Wien.

Zudem bedanke ich mich bei Frau Dr. Susanne Berger für die Korrespondenz und die zur Verfügung gestellten Instanzen.

Contents

1. Introduction

Collaborative Routing is a highly discussed topic in transportation literature, particularly in the last decade the research sector has acknowledged its theoretical and especially its practical relevance. The logistics and transportation sector has undergone fundamental changes in the past decades like intensified competition on global markets, heightened customer expectations and transforming market behavior, only to mention players like *Amazon* or *Zalando*. Among others, these alterations have led to an increased pricing pressure which negatively affects logistic providers' profit margins (Ruijgrok, 2003). Since the possible savings of internal logistic optimization are almost exhausted, research has shifted its focus on strengthening external relations along the supply chain (Skjoett-Larsen, 2000).

A very promising approach which receives augmented attention is Collaborative Routing. The surveyed cooperation occurs on a *horizontal level* between freight forwarders. In general terms the collaboration proceeds in three phases which can be classified in a systematic and temporal manner. In the first phase participating collaborators can decide either on self-fulfillment, meaning they plan and execute the orders with their own capacities, or to source out certain tasks. In the second phase the orders of participating collaborators, which are not serviced by own capacities or passed to subcontractors, are gathered in a request pool. By means of a certain allocation method these requests are dispersed among the collaborators. Prevailing methods for an efficient allocation of tasks are based on operational game theory and combinatorial auctions in order to exchange bundles of requests. In the last phase the generated profits are allocated fairly among the collaborators according to the proportionate contributions administered to the network. The operations executed in the three phases are interconnected with each other and certain procedures may appear simultaneously.

The emphasis of this thesis is based on the work of Berger and Bierwirth published in 2010: *Solutions to the request reassignment problem in collaborative carrier networks*. The authors design and solve the Collaborative Carrier Routing Problem (CCRP) by reassigning transportation requests and thus maximizing the total profit of the collaborative carrier network. They "propose a framework for a post-market based optimization, that might be implemented as an internet based electronic platform" (Berger & Bierwirth, 2009, p. 627). The integrated tour planning method constitutes a Traveling

Salesman Problem with precedence constraints (TSPPD) and is solved by exact algorithms. As the authors assume a request holds only little fractions of the vehicle's capacity, the problem corresponds to courier services in terms of a real-world environment. The authors evaluate three different collaboration strategies on a numerical basis: firstly, the freight forwarders act independently and do not cooperate, secondly, the carriers collaborate through a central planning approach and finally, coalition members establish a decentralized collaboration approach. The latter method ensures the carriers' data privacy and therefore, the authors designed two algorithms corresponding to a Vickrey Auction and a combinatorial auction. Furthermore their theoretical investigations consider three levels of competition between the carriers according to the geographical composition of customer areas.

In this thesis an alternative implementation for the CCRP is designed with the main difference of solving the routing problem heuristically. Therefore, a Double Insertion heuristic in the construction phase and a 3-opt algorithm in the optimization phase are implemented according to Renaud et al. (2000) which provide good results in a reasonable computation time. The motivation of this alternative implementation is to analyze the impact of solving the transportation problem of the CCRP heuristically and compare the results to the outcome derived by Berger and Bierwirth. Beside an in-depth analysis of the alternative implementation of the CCRP, the model of Berger and Bierwirth is extended in three different ways in anticipation of increasing the overall network profit. Additionally, the CCRP is examined for instances with more than 18 customer locations as conducted by Berger and Bierwirth.

Overall, the analysis of the alternative implementation obtains not yet reported findings in regard to the work of Berger and Bierwirth. Morevoer, the results of Berger and Bierwirth are outperformed by the implemented extensions in numerous instances though heuristics are applied in the tour planning process. In order to allow further research on the alternative implementation, the general programming structure is presented in form of illustrating major computer operations and by outlining important code fragments.

The thesis is structured as follows: In Section 2, the potential gains and challenges of collaborating carrier networks are discussed. Beyond the chance of reducing the volume of traffic and acting "green", the savings potentials for participating freight forwarders are exhibited by advancing their request portfolio in order to execute cost efficient tours and by utilizing the fleets' capacity more effectively and reducing deadweights. The discussion about the challenges on collaborative routing comprises the various difficulties of setting up a coalition and keeping the system stable. Furthermore certain threats and problems are depicted which arise in single phases of the collaboration network. In the following literature review, firstly the relevant terms and methods of the particular phases are presented according to research in context of Collaborative Routing. Secondly, the literature on Collaborative Carrier Networks is examined which cover the problem by comprising the three stages holistically.

In Section 3 the model of Berger and Bierwirth is presented and illustrated by examples in order to depict the evaluation of requests and the heuristic algorithms responsible for reassigning requests. Furthermore the applied instances by the authors are characterized. In Section 4 the results of the alternative implementation are analyzed in comparison to Berger and Bierwirth. Furthermore, the extensions for the alternative implementation are introduced and the performance is discussed. In Section 5 the program flow and the basic data structures of the alternative implementation are disclosed.

2. Collaborative Routing

In this section, the topic of Collaborative Routing is presented to provide a general overview. The reader should be aware of the high complexity of the subject, its multitudinous application spectrum, the chosen focal points and the selected perspective. The majority of articles covering the topic of Collaborative Routing are concerned about model set-ups and design questions, “based on theoretical foundations stemming from game theory, combinatorial auctions and network flow” (Dahl & Derigs, 2011, p. 77).

In the highly competitive transportation industry, freight carrier companies “can reduce their self-fulfillment costs by exploiting different execution modes” (Krajewska & Kopfer, 2006). As mentioned earlier, self-fulfillment denotes the planning and execution of transportation tasks by the carrier company itself, utilizing own vehicle fleets and capacities. Another common option for freight forwarding companies is subcontracting. Here, customer requests are forwarded to an external carrier which receives a fee for its service. In real world environments freight forwarders are subject to demand fluctuations. Hence freight carriers can choose the appropriate mode of fulfillment in an extended decision space which allows generating significant cost savings. The problem extension of incorporating subcontracting as an additional fulfillment mode is called integrated operational freight carrier planning (Krajewska & Kopfer, 2006). A common issue is that subcontractors are not able to integrate the offered request efficiently and therefore are not willing to accept the offering or only accept the request for an extended fee.

Collaborative Routing illustrates a cooperative approach to further strengthen competitiveness by enabling freight forwarder coalitions to equilibrate their request portfolios. “The purpose of the cooperation of freight forwarding entities is to find an equilibrium between the demanded and the available transport resources within several carrier entities by interchanging customer requests” (Krajewska & Kopfer, 2006). Therefore, single requests or a bundle of requests can be elected and handed over to a central request pool which is accessible for all coalition partners. The most common mode applied in collaborative routing literature solves the request reallocation problem by combinatorial auctions. Generally, the participants generate bids on single requests or on a bundle of requests to exploit economies of scope. Then by a certain auction procedure, the requests are dispersed among the bidding parties. Hence the acquired requests are part of the new request portfolio and are incorporated in the individual tour planning process.

Finally, the generated profits are dispersed among the collaborators. The allocation of profits in collaboration networks is an impartial and highly discussed stream in collaboration literature. The profit allocation needs to guarantee a fair distribution among the coalition members under the consideration that the contribution of collaborators in regard to the network may fluctuate.

2.1. Potential of collaborative routing in logistic markets

In this section, a survey on relevant figures concerning freight forwarding logistics and the potential gains offered by collaborative routing in the fast transforming logistic market is given. In regard to the company size, collaborative routing tends to address small- and medium sized companies. In Germany, 60% of the freight forwarding companies employ less than 50 employees as shown in Table 1.[1] A statement as to the optimal size of a carrier company cannot be formulated because the various conditions concerning the business activities lead to variable requirements in regard to personal and equipment capacity.

[1] If not referenced otherwise, all figures are retrieved from Zahlen, Daten, Fakten aus Spedition und Logistik, 2010

Employees per company	Up to 10	11-50	51 - 100	101-200	over 200
Companies in %	20	40	17	12	11

Table 1: Company size of freight forwarding companies in Germany. Number of employees in percent in 2010. Scale basis: 2600 companies. Representation based on Zahlen, Daten, Fakten aus Spedition und Logistik, 2010.

Interestingly, there is a significant trend of increasing the company size in terms of employees in Germany as shown in Table 2. "In the ongoing globalization process large international freight forwarding companies are more competitive than small companies due to their wider portfolio of disposable resources and a higher ranking in the market power structure. The remedy for the medium- and small-sized carrier businesses is to establish coalitions" (Krajewska & Kopfer, 2006, p. 301) or to increase the company size.

Year	1985	1990	1995	2000	2005	2010
Companies with more than 50 employees (in percent)	17,5	20,3	24,5	32,0	30,0	40,0

Table 2: Company size of freight forwarding companies in Germany according to the number of employees. Representation based on Zahlen, Daten, Fakten aus Spedition und Logistik, 2010.

In the business area of freight forwarding, the most executed transport mode in Europe still is road haulage, especially in the less-than-truckload cargo transportation. About 54% of freight forwarding companies operate in this market segment and about 25% identify this line of business as their main field of activity. The trend for less-than-truckload movements is strengthened by a transforming order pattern in industry and retail markets requiring a just-in-time fulfilment of demand. Thus order quantities decline, the re-procurement frequency is shortened and traditional storage practices become less important. Looking at the proportion of freight forwarders operating with an own vehicle fleet, about 51% of long-distance hauling freight forwarders utilize their own trucks. But the role of outsourcing transportation activities in Germany and international cargo business increases continuously. In Germany, the share of carrier companies engaging services from external carriers increased from 73% in 2005 to 76% in 2010.A further examination of carrier collaboration in Germany is provided by Dahl and Derigs (2011). According to their research, the market value of the courier/express segment in Europe was about 36 billion Euro in 2001, whereby 30% of this volume was realized in Germany. There are nearly 10.000 forwarding enterprises in Germany which specialize in general freight transportation, among which a large number is attributed to one-person businesses acting as sub-contractors for larger firms only. Therefore, a Cooperative Logistic Network (CLN) was established in 2001 to build an alliance under a strong brand for small- and medium sized companies. By initiating this cooperation, CLN is capable of serving pickup and delivery shipments in Germany within 60 minutes and 365 days a year. “The purpose of CLN […] is to realize a profitable equilibrium between customer demand and available transport resources by interchanging customer requests among partners” (Dahl & Derigs, 2011, p. 621). As a member of CLN, the freight forwarders gained two options to serve a task to the customer, either by self-fulfillment or by outsourcing the request to a coalition partner paying a compensation price. The performance indicator for the CLN is implied by the crucial factor of the percentage of deadheads. Previous to the initlization of CLN, the number of deadhead was measured to the enterprises’ experience between 40% and 45%. This inefficient degree of capacity utilization resulted from “the high spatial diversity of the single requests and the inability to consolidate within the available time-frame, yet, a number much too high to allow competitive prices and sufficient profit” (Dahl & Derigs, 2011, p. 621). After their first experiences, the aim of the members was to establish a percentage of 30% deadweights, because even the mutual growth and exploiting the full coordination potential cannot overcome the extremely short reaction time.

Beside cost savings due to exploiting economies of scope in terms of minimizing empty travel miles, cost savings are gained by economies of scale by integrating several requests into one tour. Furthermore, “resource sharing will help to build more reasonable transportation plans to better utilize vehicles, reduce travel time, unloaded distance and lower the total transportation cost effectively” (Zhang, Xu, Yu, & Lui, 2009, p. 259). Cost savings due to collaborative routing commonly range between 5% and 15% (Cruijssen & Salomon, 2004). Further theoretical and real-world findings are depicted in Section 2.3.4.

2.2. Challenges on collaborative transport planning

This section points out the difficulties arising by initiating and executing collaboration networks between freight forwarding companies. A wide set of difficulties occur, such as building and setting up coalitions between competitors on a tactical and strategic horizon and keeping the system stable in regard to the information- and communication-transfers required on the operational level. Furthermore, there is a wide range of uncertainties in regard to data privacy and a fair profit allocation. Moreover, collaboration networks can suffer from information asymmetry and collaborators underlie different objectives and constraints (Stadtler, 2009, p. 5). Although all these factors impact the setup of a network program, it is necessary to guarantee a profitable and efficient network structure for the participating collaborators. Beneath the microeconomic factors appearing in a collaboration network, macroeconomic circumstances also affect the carrier's scope of action just as for example gas prices impact the transportation rates (Meixell & Norbis, 2008). The paper of Kopfer and Wang (2011) provides a proper insight into the challenges related to collaborative transport planning.

First of all, the authors address the real world application problem of measuring the profit generated by the whole coalition and the participators. Two main difficulties are identified for determining the potential cost-savings: Firstly, the disclosure of private company information to a central planning instance. Hereby the participants are prompted to reveal internal information regarding capacities and cost structures. Secondly, the development of a real world algorithm solving the Carrier Collaboration Network Problem which is a NP-hard global optimization problem, still is hard to realize.

Furthermore, the authors allude to the hard to implement real-word factor of the participants' autonomy. The coalition partners pursue diverging organizational and business strategies. Hence, the individual targets of the collaborators can differ with respect to the coalition's objective to maximize its benefits in total. In game theory literature, the problem of giving individuals sufficient incentives in collaboration networks is denoted as the incentive compatibility problem. In addition, the companies' autonomy allows a superior utilization of local knowledge. "Both individual strategic preferences and local information can be formulated as lots of additional restrictions for the aggregated central planning problem" (Wang & Kopfer, 2011). Consequently, the authors state the very challenging objective to reflect all these restrictions in a dynamic environment, which requires the development of a "super-algorithm".

Another factor hampering the determination of the potential savings are transaction costs like setup costs, bargaining and execution. Until now, the research literature hardly surveyed the impact of transaction costs in context of collaborative routing. The involved cost objects such as initiating, bargaining and execution costs can have an unequal impact on the participants and result in varying net benefits within the coalition.

Furthermore, Wang and Kopfer (2011) identified the challenges of designing a model for carrier collaboration networks, considering the three phases of the framework holistically.

Therefore, the authors discuss the generally required guidelines and the three phases, *preprocessing*, *exchange mechanism* and *profit allocation* in detail.

2.2.1. General guidelines for establishing a carrier collaboration

The general guidelines comprise the freight forwarders' incentives for joining a carrier collaboration which rely on the following:

1.) the conducted payment by a carrier for executing a coalition member's request is less than the potential cost,
2.) receiving a higher payment for a partner's request in contrast to the self-fulfillment costs, and
3.) receiving the shared mutual profits.

These conditions need to be concretized and implemented into the collaboration network design over the three different phases simultaneously. Hence the most important goal for the participants of a collaboration network is to derive cost-saving potentials and to fully exploit them. Therefore, the coalition members must identify complementary request portfolios in order to achieve synergy effects by optimally utilizing the interaction of offered requests and capacities. "For this purpose, coalition has to provide participants both sufficient information for their local decision-making processes and enough incentives for cooperative behaviors" (Wang & Kopfer, 2011, p. 6).

Another crucial term of keeping the collaboration network stable is the notion of fairness. It is hard to provide an absolute definition of fairness as long as coalition members advance individual preferences in respect to data privacy issues, delegating decision competences or the allocation of profits. Wang and Kopfer identified several aspects in order to ensure "fairness" in a carrier collaboration network:

- "No one has to expose more private information than others.
- No one has to give up more competences than others.
- All contributions to the coalition, especially to a successful exchange leading to a win-win situation, should be awarded.
- The award for participants depends only on their contributions, but not on other characteristics.
- Same contribution has to be equally awarded" (Wang & Kopfer, 2011, p. 6).

Ultimately, the network design is obligated to be consistent in terms of fairness for each collaboration participant to ensure that carriers are willing to enter the collaboration network and the system is stable on a long-run perspective.

2.2.2. Preprocessing

In regard to the major challenges which arise in the single phases of collaboration networks, the main task in the first phase is to identify which request is offered to the central request pool and to determine the proper transfer price. The former decision is performed autonomously by the carriers in context of a decentralized collaboration network. Nevertheless, the modality of selecting the requests constitutes an important element in the network design and is supposed to facilitate the carriers' decision process of outsourcing (bundles of) requests. The evaluation of the quotation price for requests and bundles of requests is hard to be incorporated holistically in the collaboration framework. Usually, the price determination is based on the combination of the potential costs a carrier incurs for servicing a request in a certain tour and the customer transfer price that the carrier receives. As long as this data is not available in a decentralized network, the framework must provide sufficient incentives for carriers to avoid an egoistic price determination.

2.2.3. Exchange mechanism

The challenges referred to the exchange mechanism rely on reassigning requests in a manner which maximizes the entire collaboration's profit by exploiting cost-saving potentials efficiently. Hereby, the success of the exchange mechanism is contributed by combining single requests into bundles which creates a synergy effect and depicts attractive vehicle routes. The composition of bundles is a sophisticated operation as requests may occur in various bundles and bidding parties face a certain risk of not obtaining the entire bundle. The risk of acquiring only a subset of a bundle which leads to a decreasing synergy effect is denoted in multi-object auctions as the Exposure Problem. Furthermore, the exchange mechanism must overcome the threat of participants acting "non-cooperatively" during the reassignment procedure. This must be the case not only for participants who consciously take advantage, but also for coalition members who behave improper due to a lack of experience. Moreover, the design of the auction model is obligated to take into consideration the degree of decision competencies and private data which are conveyed to the mediator. According to the grade of autonomy of the coalition members and the mediator, the setup configuration of the exchange mechanism may vary which proves as a very challenging problem in order to meet the expenses of all participants.

2.2.4. Profit allocation

Finally, the profit sharing scheme as the last component of the carrier collaboration model allocates the generated profit fairly among the coalition members. The main challenge is to identify the partial contribution each participant provides for the collaboration outcome. “This identification has to be done both for the successful and profitable exchange for the short-run and for the sustainability and stability of the coalition for the long-run. After that, all identified elements must be given an appropriate weight, representing the evaluation of the importance of these identified contributions” (Wang & Kopfer, 2011, p. 9). In addition, the collaborating carriers underlie varying conceptions in terms of a fair profit allocation due to distinct business strategies and philosophies. Besides, the question arises how deep the profit sharing scheme is incorporated and retrieves information from earlier phases. Consequentially the profit allocation scheme must be transparent in order to provide a clear traceability of the rewarding procedure.

2.3. Literature review

In research literature, there is a vast number of approaches which examine a single phase in detail, especially for the first phase of identifying a carrier's planning decision to outsource certain requests to an external party and the second stage of reassigning (bundles of) requests. The first part of the literature review will give an overview of actual research papers which are contributed to the topic of carrier collaboration networks and examine partial phases in detail. The methodology encompasses a description of the applied methods and the problem-configuration is denoted. In the second part, the review focuses on research papers which discuss collaborative routing networks holistically.

2.3.1. Request selection in collaborative routing

In strictly decentralized collaborative carrier networks, the freight forwarders are obligated to identify autonomously such requests which cannot be integrated efficiently into their operational planning scheme. In transportation literature, there are various methods which address the problem of selecting disadvantageous transportation requests in terms of outsourcing them to an external party. The approach of integrated operational freight carrier planning where freight forwarders face two alternatives for executing exhibited requests, either by self-fulfillment or by sub-contracting requests to external carriers has already been introduced in Section 2. An in-depth problem description is provided by Krajewska & Kopfer (2009). They outline the manual planning process of a scheduler as follows: In a first step, the scheduler identifies the most attractive requests and assigns them to the own vehicle fleet. "The attractiveness of a request is estimated on the basis of its proportionate profit contribution" (Krajewska & Kopfer, 2009, p. 742). Therefore, the round trips of the vehicles are constructed feasibly according to pick-up and delivery locations and further constraints like vehicles' capacity and time-windows at the customer locations. The costs are composed of outstanding fixed costs including amortization costs, fees and driver payments. The marginal variable costs are considerably low and calculated by a travel-dependent cost-rate per travel unit. The goal of the freight forwarders is to exhaust the capacities the own fleet.

In the next step, unattractive requests are forwarded to a sub-contractor. Therefore, the authors describe the various forms of sub-contracting which rely on the frequency a sub-contractor is utilized. The classification ranges on a scale from one independent engagement to an exclusive subcontractor partnership. The authors solved the problem by an elaborated Tabu-search heuristic. Other recent and significant contributions to this topic are provided by Chu (2005) applying a modified savings algorithm and by Bolduc et al. (2008) composing a perturbation metaheuristic. A broad comparison of similar approaches is examined by Kopfer and Krajewska (2007).

There are various other streams in transportation literature, which discuss the first phase relevant task in collaborative routing networks of excluding customer nodes in tours, like the Traveling Salesman with Profits (TSPP). The TSPP is a generalized form of the TSP, where the constraint of visiting all customer nodes is relaxed and to each vertex a profit is associated. The goal is the simultaneous optimization of minimizing the routing costs and maximizing the collected profit. Here, two different schools of solving the TSPP evolved: firstly, the single objective problem where both objectives are combined in the objective function or one objective is treated as a constraint. A comprehensive literature survey in regard to this problem is provided by Feillet et al. (2005).

In case a constraint is introduced as an additional boundary exhibiting a maximum allowed tour length and the goal is to maximize the collected profit or rather the score, the problem is designated as the Orienteering Problem (OP). Vansteenwegen et al. compiled a survey for the OP in 2011. Secondly, the TSPP can be solved as a bi-objective combinatorial optimization problem. Jozefowiez et al. (2008) “find solutions to this problem using the notion of Pareto optimality, i.e. by searching for efficient solutions and constructing an efficient frontier” (p.177).

Another stream of research discussing the exclusion of inefficient transportation requests is conducted by the Selective Pickup and Delivery Problem (SPDP). In contrast to the problem formulation of the ordinary pickup and delivery problem, two features hold for the SPDP: Firstly, the forceful constraint that all pickup customer nodes need to be visited is relaxed. Secondly, an additional capacity constraint in regard to the vehicles’ load is imposed. The SPDP is classified as a many-to-many problem according to Berbeglia et al. (2007), meaning that “each node serves as either a source (pickup) or a destination (delivery) of commodities; and the commodities collected from pickup nodes can supply any delivery nodes” (Ting & Liao, 2013, p. 199). This application setup is rather attractive for logistic providers which service (some) pickup customers and are obligated to satisfy all delivery customers. Ting and Liao (2013) propose the example of distributing rental bikes for city tours. The route of the truck can be planned most

efficiently if only some pickup locations for bikes are visited and it is not necessary to pick-up bikes at *all* rental stations to fulfill the demand of the delivery stations. Another article covering the topic of the SPDP is offered by Falcon et al. (2010), who solved a many-to-many version of the carrier-based coverage repair problem in wireless sensor networks by an ant colony approach. A literature survey on the SPDP is provided by Ting and Liao (2013).
The applied problem settings in collaborative carrier routing approaches can be classified as one-to-one problems according to Berbeglia et al. (2007). That means the commodity of a pickup customer satisfies the needs of one respective delivery customer. In research literature, so far no selective pickup and delivery problem was solved for the one-to-one pickup and delivery problem servicing *n* (number of customers) commodities (Ting & Liao, 2013, p. 200).

2.3.2. Combinatorial auctions in collaborative routing

In the following section, an overview of relevant papers in regard to combinatorial auctions for transportation requests is presented. In an obsolescent reassignment process, carriers attend an auction to bid on individual requests of interest. Each carrier determines the bid value autonomously by means of several factors, like the marginal tour lengths, price and business requirements. The more sophisticated approach is to bid on a bundle of requests in order to obtain economies of scope. “That is, a carrier may desire to bid on separate lanes that collectively represent a cost efficient service route with respect to minimizing empty miles travel and other repositioning costs. […] In short, carriers seek a set of lanes that are synergistic with respect to repositioning costs” (Lee, Kwon, & Ma, 2007, p. 173). As already mentioned above, the risk that carriers face of not obtaining the desired request bundle because requests are allocated separately is called the Exposure Problem (Kwasnica, Ledyard, Porter, & DeMartini, 2005). “The exposure problem can prevent auctions from achieving high levels of efficiency since bidders may be reluctant to bid aggressively for items in fear of not obtaining a complete set of items which can make generation of revenue difficult for the auctioneer and allow others to obtain items for lower prices” (Lee, Kwon, & Ma, 2007, p. 174). Combinatorial auctions can overcome the exposure problem by allowing bids on single items as well as on a bundle of items. In case of transportation procurement, a bidding carrier receives the bundle of requests entirely if the bidding price is accepted or the bid is rejected and none of the items contained in the package are acquired. Such advancement minimizes the risk of just obtaining a subset of requests which fits into the current request portfolio inefficiently. Hence combinatorial auctions are a proper exchange mechanism for allocating transportation requests more efficiently. Especially the demand of carriers to generate synergetic preferences in the bidding phase can be fulfilled and a too aggressive bidding strategy on separated items is avoided.

The auction environment describing the general auction context is denoted according to Lee et al. (2007). In the initialization phase of a transportation network, the carriers negotiate the relevant terms and conditions for an auction framework. Hence, in established auction environments carriers submit and generate bids to the auction agent. The auctioneer is tempted to solve the Winner Determination Problem (WDP). The WDP is a NP-hard combinatorial optimization problem which usually is a variant of the weighted set packing problem and examined in detail by de Vries and Vohra (2003). In case that a single-round auction is applied, the WDP is terminated after a single computation whereas in a multi-round auction the bidding phase and WDP can be repeated as long as no termination criteria are fulfilled, as shown in Figure 1.

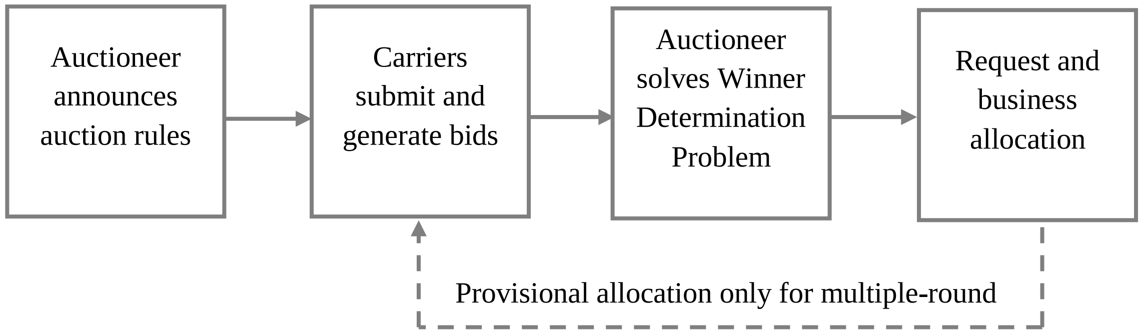

Figure 1: The general structure of single- and multi-round auctions. Representation based on Lee et al., 2007, p. 176

The latest publication in regard to bid generation problems in combinatorial auctions was released by Triki et al. in 2013. The authors provide a comprehensive literature review for this field of study and "deal with the generation of bundles of loads to be submitted by carriers participating in combinatorial auctions in the context of long-haul full truckload transportation services" (Triki, Oprea, Beraldi, & Crainic, 2013, p. 1). The authors designed a probabilistic optimization model in order to integrate the issues of pricing and bid generation in the framework of routing planning conducted by freight forwarding companies.

2.3.3. Profit allocation in collaborative routing

The literature review is rounded off in the following section, by pointing out the most significant contributions in regard to profit allocation in collaborative transportation networks. In case of horizontal cooperation between carriers, the generated profit during the collaboration process needs to be allocated among the coalition members in concern with agreed conditions. In order to ensure a long-term stability of such a profit allocation structure, an appropriate incentive scheme is obligatory for the coalition members in the collaboration process. The incentive scheme implies that each collaborator takes a financial advantage of participating in the coalition and the generated profits are distributed fairly. "The features to be included in the profit sharing scheme depend on the distribution of power among freight carriers, on their level of interdependency and willingness to make compromises, and on the market within which they operate" (Krajewska M. , Kopfer, Laporte, Ropke , & Zaccor, 2008, p. 1483). Furthermore the profit allocation mechanism is obligated to respect the proportionate contribution each coalition member provides in the collaboration.

The basic concepts for solving the profit allocation problem are reviewed in reference to Zhang et al. (2009). The most commonly applied solution method is the *Proportional Allocation.* The collaborative profit/cost savings are distributed equally among the collaborators and are weighted according to each freight forwarder's stand-alone costs. The method proves as easy to configure and implement, but consigns deficits in terms of the cooperative game theory as it is not guaranteed that each alliance member is better off.

Another common practice to solve the profit allocation problem is the *Shapley Value.* It is able to track the average marginal contribution each collaborator facilitates to the network and also respects the aspects of bargaining power. "Shapley Value is the unique allocation method to satisfy three axioms: dummy, additivity and equal treatment of equals" (Zhang, Xu, Yu, & Lui, 2009, p. 261). However, in many instances the instability of the Shapley Value is reported.

Another mentionable solution approach is *Nucleolus*, which “is the cost allocation that lexicographically minimize the maximal excess, the difference between the total allocated profit to a subset and the stand alone cost of that subset, over all the subsets of the collaboration“ (Zhang, Xu, Yu, & Lui, 2009, p. 261). But the *Nucleolus* takes into account neither the proportional contribution of a collaborator nor the relative cost savings.

Furthermore, the *Core* is one of the most reputable notions in context of fair allocation of profits/costs in cooperative game theory and shows similarities to the Nash equilibrium of the non-cooperative game theory. “An allocation of benefits is said to be in the core if the sum of the payoffs over all players is their maximum attainable profit (budget balance property) and no subset of players can collude and obtain a better payoff for its members (stability property). […] An allocation in the core helps the grand coalition to be perceived as fair and not be threatened by its subcoalitions” (Agarwal & Ergun, 2010, p. 1729). Consequently, the profit allocation in the core provides a strong stability, but it is rarely applied in transport collaboration literature.

Research papers discussing the profit allocation mechanism solely in context of carrier collaboration are uncommon because the topic depends heavily on the previous phases of outsourcing tasks and the method of reassigning requests. An entirely new mechanism in the area of carrier collaboration for solving the profit allocation problem is proposed by Zhang et al. (2009). The authors designed the Weighted Relative Savings Model which provides “a stable allocation that minimizes the maximum difference between relative savings among the participants and also reflects the contribution difference“ (Zhang, Xu, Yu, & Lui, 2009, p. 261). Furthermore, the model respects the degree of independencies among the freight forwarders and the willingness of carriers to form compromises on the prevailing market which they operate in. The approach of Schönberger (2005) discusses a loss sharing model rather than a profit sharing model, in the framework of operational freight carrier planning, but the method is not capable of preserving the individual interests of freight forwarders (Krajewska M. , Kopfer, Laporte, Ropke , & Zaccor, 2008, p. 1484).

2.3.4. Carrier collaboration covering the three relevant phases holistically

A major article in the sector of collaborative routing is composed by Krajewska and Kopfer (2009). Their work bases on the approach of the integrated operational transport problem already mentioned. Hence, freight forwarding entities have the option to either service requests by self-fulfillment utilizing their own capacities or to outsource the orders to a sub-contractor. In case of self-fulfillment, the forwarding entities solve autonomously, a capacitated pickup and delivery problem with time windows (PDPTW) for homogenous vehicles. For both options the marginal costs of a single request are computed as the costs which arise for servicing the additional request, whereby the authors do consider single and also bundles of requests. In case of outsourcing requests to a subcontractor, the costs are additionally calculated by incorporating the according tariffs which depend on distance and loading weight.

The collaboration process takes three phases: In the preprocessing step, each forwarder computes the costs for each request that they offer to collaboration partners. In the profit optimization phase the collaboration partners set up a mapping of requests and the reassignment of requests is carried out by solving the Combinatorial Auction Problem. In the profit sharing phase in terms of the cooperative game theory, the benefits are allocated among the individual decision makers. Results are presented in form of an example. The presented collaboration model is based on the combinatorial auction theory and also on the operations research game theory. It constitutes the theoretical framework for request exchange, profit optimization and profit sharing for an alliance of freight forwarding entities. In regard to the incentive scheme of collaborators announcing true assessments, the authors argue on the one hand that bids are placed on a bundle in order to receive it. On the other hand, the authors mention that "the partners are often inter-connected to each other by the formalized market structures, e.g. the partners represent the Profit Centers of one company or holding" (Krajewska & Kopfer, 2006, p. 307).

Schwind et al. (2009) designed a combinatorial exchange mechanism called *ComEx*, which exploits synergies for combining transportation routes of various carriers. The implementation reflects an intra-enterprise reassignment of requests for a logistic company which is composed of geographically dispersed profit centers. The transportation planning scheme bases on the Vehicle Routing Problem (VRP) and the requests comprise either pickup or delivery tasks. The decision support system reassigns requests by an iterative combinatorial auction structure while the agent has total information access. The profit calculations are neglected due to the profit center structure of the network. The authors report cost savings in a real-world example of up to 14% for the entire network of a medium-sized logistic company.

Ackermann et al. (2011) published an article related to Krajewska & Kopfer (2006) and Schwind et al. (2009) in which a deepened focus is put on the reassignment of request bundles executed by combinatorial auctions. The goal of the authors is to establish an effective system in a practical environment of less than truckload carriers. In regard to the vehicles' capacity the authors assume big freight loads which allow a vehicle to service two to five units at once. The exchange procedure of requests deviates slightly from the classical chronology and is processed in four stages. In the *offering phase* the carriers place their bids on a platform where the coalition members gain access on the requests and in the *bidding phase* the bids are placed on the requests. In the *reassignment phase* the Winner Determination Problem is solved which determines the proper reassignment of requests among the collaborators. Finally the generated profits are allocated among the coalition members in the profit *sharing phase*.

The authors argue that splitting up the user interaction Steps 1 and 2 is not crucial "as long as participants do not regret decisions from phase one in phase two, when they receive additional information" (Ackermann, Ewe, Kopfer, & Küfer, 2011, p. 4). Furthermore, the system complexity is reduced by separating both steps. The authors emphasize the strict conversion of respecting the data privacy of the coalition members and the fair allocation of profits. The experimental results show cost savings for their self-generated instances of up to 27,6% and 4,3% for the real-world data based on a profit center structured German company.

The work of Bloos and Kopfer (2011) concentrates on the individual perspective of a carrier rather than of the whole network as it is the case in Berger and Bierwirth (2009), Krajewska and Kopfer (2006) and Schwind et al. (2009). Furthermore, the authors argue that the underlying optimization problem is stochastic because the operational planning activities depend on the coalition partners' decisions and on the (human) behavior according to their strategies. The problem consists of cooperating carriers, whereas each carrier company owns a homogeneous vehicle fleet with constraints in loading capacity. The authors assume that the vehicles' capacity of all participating carriers is sufficient to fulfill the total network demand. The requests are served to the customer locations in form of less than truckload, pickup and delivery requests (LTL-PD). The model aims to reduce the costs by reassigning requests among the carriers, so that the tour length of the network is minimized. After solving the carrier's optimization problem, the authors introduce two kinds of heuristic methods which provide an indicator for the carriers to assess the requests at their side. The *evaluation based criterion* simply identifies the round-trip based distance if a certain carrier executes a request. The isolation based criterion "considers the distance between vehicle and LTL-PD request as well as the distance to other locations as they may have to be reached within the same tour" (Bloos & Kopfer, 2011, p. 134). The evaluation criteria serve as the planning method which solves the collaborative planning problem. The results are analyzed in form of a small empirical study and compared to a central planning approach which is a global optimum due to complete network transparency. The solution quality of the decentralized planning method deviates only 5 to 10% related to the central planning approach.

Dahl and Derigs (2010) established a collaboration network based on the coalition of independent express carriers on an operational level. In contrast to related papers, the problem environment is highly dynamic and the exchange of requests is executed instantaneously. Therefore, the authors decided to implement a real-time internet-based collaborative Decision Support System (DSS) for a real-world example of a carrier-network. The orders are based on LTL-PD requests and "the transfer payments between the exchanging carriers are calculated with the help of underlying, distance-dependent cost functions" (Bloos & Kopfer, 2011, p. 134). The empirical analysis proves the effectiveness of the real-time DSS in an express carrier network. Provided that an adequate compensation schema is applied, the authors derive nearly the output generated by a central planning approach.

Dai and Chen (2011) propose a carrier collaboration approach considering a multi-agent and auction-based framework, where pickup and delivery requests are served in means of less than truckload transportation. The *request selection problem* the carriers face for the outsourcing decision of a request and the *request bidding problem* are both formulated as mixed integer programming problems. The problem setting is "decentralized, asynchronous, and dynamic, where multiple auctions may occur simultaneously and interact with each other" (Dai & Chen, 2011, p. 101). The authors evaluate the performance of their model by randomly generated instances and compare the outcome to a central planning and a non-collaborative approach. Hereby the authors show that in most instances the profit of each carrier and the entire network profit can be increased by reducing the transportation costs.

In the work of Krajewska et al. (2008), a combination of routing and scheduling problems and of cooperative game theory is surveyed. The authors analyzed a medium-sized freight forwarding company which consists of several autonomous profit centers behaving as usual competitors. Each profit center owns a fleet of vehicles and maintains a long-term partnership to several sub-contractors. In case of only considering sub-contractors in the outsourcing procedure for unprofitable requests, a high percentage of deadhead truck-movements occur. The authors aim to depict the benefits of collaboration in terms of incremental profits and apply the principles of game theory for a fair profit allocation in terms of the Shapley Value. The problem setting is a PDPTW, but due to merging the request portfolio of all participants, a multi-depot PDPTW version is solved over the total customer set. The cost savings of the collaboration yield 10% to 20% over the non-cooperative approach.

3. The implementation of Berger and Bierwirth

The implementation of this thesis is based on the setup of Susanne Berger and Christian Bierwirth published in the paper "Solutions to the request reassignment problem in collaborative carrier networks" (2009). In the following section an outline of the problem, labeled as the Collaborative Carrier Routing Problem (CCRP), is presented. The problem formulation is recapitulated according to Berger and Bierwirth[2].

3.1. The Collaborative Carrier Routing Problem

The carriers receive transportation requests from either "shippers, typically manufacturers and retailers, or large carrier organizations as sub-contractors" (p. 627). The routing of the trucks' tour is planned on a daily basis. Due to the successive planning it may occur that a request "cannot be efficiently integrated into the route of a carrier. In this situation, a post-market and optimization-based collaboration can yield a reassignment of the requests which improves both, the overall efficiency of the network and the individual profit of

[2] Unless otherwise specified, all denotations and quotes in the following section are referenced from Berger & Bierwirth (2009)

each single carrier" (p. 627). The auction setup can be seen as an "internet based electronic platform" (p. 627).

The main target of the framework is "to maximize the overall profit of the network with as few as possible information transfer, because carriers disclose customer information unwillingly" (p. 627).

Furthermore the authors introduce three different collaboration strategies for evaluating the impact on the network profit:

a. the carriers do not collaborate,
b. the carriers collaborate through a decentralized planning approach, and
c. the carriers collaborate through a central planning approach, where full information is needed.

For strategy (b) the authors set up two kinds of algorithms for reassigning requests: firstly, a Vickrey auction, which reassigns one request at a time, secondly a combinatorial auction, which includes bundling effects of several requests. Strategy (c) presumes a total transparency of information which leads to a Multi Depot Traveling Salesman Problem with Pickup and Deliveries (MDTSPPD).

Furthermore Berger and Bierwirth examine the degree of competition between the carriers "by varying the geographical separation of their customer areas in three steps (adjacent, overlapping, identical)" (p. 628).

3.2. The occurring transportation problem

The problem configuration consists of a collaboration network of carrier companies. The underlying transportation problem, which all carriers are prompted to solve autonomously, is a Traveling Salesman Problem with Pickup and Deliveries (TSPDP), containing one-to-one precedence constraints between the pickup and the respective delivery customer. Hence, in a tour the pickup customer (PC) must be served prior to the appendent delivery customer (DC). The carriers operate with a homogenous fleet of one vehicle each and an individual depot. For simplification purposes the authors take small goods to be conveyed as a basis, leading to the presumption that capacities are not considered.

3.3. Profit determination without collaboration

The profit calculation scheme for evaluating requests incorporates the revenues obtained by the carriers from the shippers and the costs of carriers servicing the customers in a certain tour. Therefore, Berger and Bierwirth provide the following notation:

M	the member set of the carrier network, $M = \{1,2, \dots m\}$
N	set of all requests to be served in one period, $N = \{1,2, \dots n\}$
N_i	set of requests contracted by carrier $i \in M (N = \cup_{i \in M} N_i)$
r_j	revenue of request $j \in N$ paid by a shipper
c_{ij}	marginal cost of carrier $i \in M$ to serve request $j \in N$
p_{ij}	marginal profit of request $j \in N$ for carrier $i \in M$
d_j	direct traveling distance of request $j \in N$
α_1, α_2	base rate and distance dependent transportation rate per kilometer
l_{ij}	marginal tour length of request $j \in N$ for carrier $i \in M$
β_1, β_2	stopping cost per request and traveling cost per kilometer
$L(N')$	minimum tour length needed to serve a set of requests N'
R_i	total revenue of carrier $i \in M$ gained for serving N_i
C_i	total cost of carrier $i \in M$ incurred from serving N_i
P_i^0	total profit of carrier $i \in M$ obtained without collaboration
P_i	total profit of carrier $i \in M$ obtained for serving request set N_i
P	period profit of the network
v_j	compensation price for request $j \in N$ in a forward auction
ΔP	profit gain of the network, achieved by a reassignment of request

3.3.1. Original instances and constants

Based on the denotations presented above, the process of deriving the network profit is illustrated in form of an example. Table 3 shows all of the data available in instance #74 created by Berger and Bierwirth[3]. The authors choose price rates for deriving the charge

[3] Mentioning request 3 of Carrier 1: pickup customer location equals the delivery customer location. Such a constellation appears seldom due to the randomly drawn instances by Berger and Bierwirth

of revenue with a fixed transportation rate $\alpha_1 = 20$ and a distance dependent transportation rate $\alpha_2 = 2$. The stopping costs are given by $\beta_1 = 10$ and a cost per kilometer of $\beta_2 = 1$.

Characterization of Node	Carrier 1	Carrier 2	Carrier 3
	X | Y	X | Y	X | Y
Depot	57 | 29	30 | 60	18 | 24
P 1/4/7	45 | 65	55 | 5	53 | 12
D 1/4/7	53 | 12	26 | 52	45 | 65
P 2/4/8	30 | 5	13 | 52	32 | 12
D 2/4/8	57 | 48	53 | 52	37 | 47
P 3/5/9	30 | 25	53 | 12	45 | 20
D 3/5/9	30 | 25	37 | 47	20 | 20

Table 3: Instance #74 of Berger and Bierwirth containing all available data.

3.3.2. Revenue of a request

$$r_j = \alpha_1 + d_j \alpha_2 \tag{1}$$

$$R_i = \sum_{j \epsilon N_i} r_j \tag{2}$$

To determine the revenue of a request, the distance d_j between the pickup and related delivery customer is calculated by the Euclidean Distance $d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$ and passed to (1). Table 4 shows the revenue of request pairs r_j. The accumulated revenues r_j of a carrier result in the total charge R_i a Carrier can obtain by servicing all requests (2).

Request	Carrier 1	Carrier 2	Carrier 3
1/4/7	127,2	130,5	127,2
2/4/8	121,5	100,0	90,7
3/5/9	20,0	97,0	70,0
R_i	268,75	327,42	287,91

Table 4: The charges $\boldsymbol{r_j}$ for all requests and the total revenue $\boldsymbol{R_i}$ a carrier can obtain

3.3.3. Marginal cost of a request

$$c_{ij} = \beta_1 + l_{ij}\beta_2 \quad (3)$$

$$l_{ij} = L(N_{i)} - L(N_i \backslash \{j\}) \quad (4)$$

$$C_i = \sum_{j \in N_i} \beta_1 + L(N_i)\beta_2 \quad (5)$$

For the cost determination the authors mention that “in transportation markets, the paid charges typically hide the true cost of service creation” (p. 628). So the authors define the self-fulfillment cost c_{ij} as the marginal cost of carrier $i \in M$ to serve request $j \in N_i$.

The evaluation of the marginal cost of a request is calculated in a two-step procedure.

In a first step the marginal tour length of a request is calculated by equation (4). The term l_{ij} denotes the marginal tour length of request j, meaning “the additional traveling distance for carrier i to serve request j. The marginal tour length is computed by the difference of the tour lengths required to serve the request set N_i including and excluding request j” (p.630). The function L(.) returns the optimal tour length of the surveyed route. Table 5 presents the calculations to derive the marginal tour length of requests for Carrier 1 and its original tour is visualized in Figure 2. The second row shows the tours without the surveyed request and the third row reflects the respective tour lengths. The original tour length is derived by (5) and yields 173,3. Next the marginal tour length of a request l_{1j} can be determined by subtracting l_{1j} from the original tour containing all requests (4). The marginal cost of a request is concluded by equation (3).

Request *j*	P1-D1	P2-D2	P3-D3
Tour w/o request	0-P2-P3-D3-D2-0	0-P1-P3-D3-D1-0	0-P2-P1-D2-D1-0
$\boldsymbol{L(N_i \backslash \{j\})}$	110,6	124,6	172,5
$\boldsymbol{l_{1j}}$	62,7	48,7	0,8
$\boldsymbol{c_{ij}}$	72,7	58,7	10,8

Table 5: Deriving the marginal costs $\boldsymbol{c_{ij}}$ of requests *j* possessed by Carrier 1.

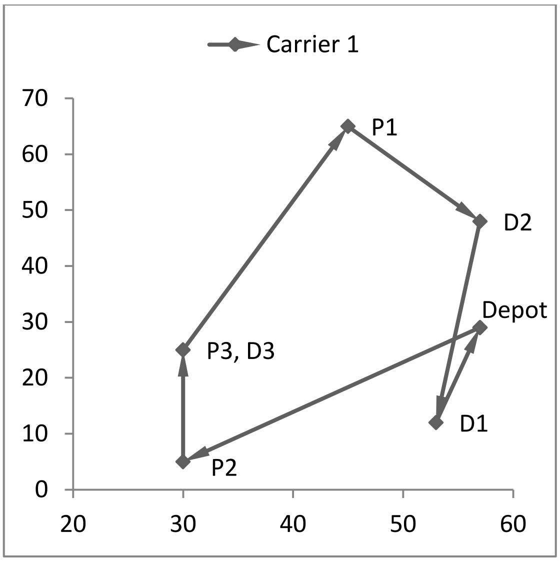

Figure 2: Initial tour of Carrier 1 with tour length 173,3

3.3.4. Marginal Profit of a request

$$p_{ij} = r_j - c_{ij} \quad (6)$$

$$P_i^0 = R_i - C_i \quad (7)$$

$$P = \sum_{i \in M} P_i^0 \quad (8)$$

The evaluation of requests is concluded by the calculation of the marginal profits executed in equation (6). Thereupon a carrier's total profit P_i^0 is determined by equation (7) and the total network profit P generated by all collaborators is given by equation (8). The marginal profit of all requests owed by the carriers is denoted in Table 6.

Request j	p_{1j}	p_{2j}	p_{3j}
1/4/7	55,5	100,4	63,9
2/4/8	62,8	50,3	77,0
3/5/9	9,1	84,9	50,7

Table 6: Marginal profits of requests for all participating carriers

3.4. Subcontraction of requests

In a Collaborative Carrier Network (CCN), the participating carriers $i \in M$ have two options to deal with the possessed requests N_i: either to service a request by self-fulfillment or by subcontracting the request to another carrier in the network. Generally, subcontracting is preferred if a request turns out to yield low marginal profits.

Assume a Carrier k buys a request j from a shipper at price r_j, like illustrated in the schematic representation of Figure 3. In addition another carrier i is capable to serve this request at lower marginal costs $c_{ij} < c_{kj}$. The framework enables carrier k to sell the request to carrier i in a forward auction. Carrier i pays a compensation price v_j to carrier k. In a forward auction the compensation price serves as floor price, expressing the minimum price Carrier i is willing to pay for acquiring the request. In such a constellation, the compensation payments carried out between the carriers only serve as internal transfer prices and do not affect the period profit of network P.

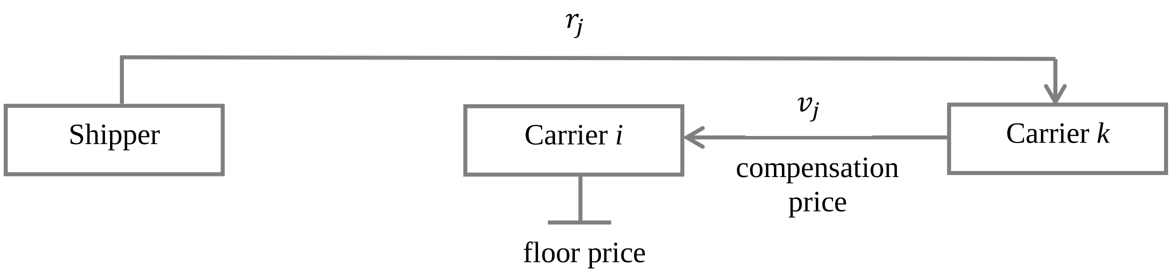

Figure 3: Cash flows for sub-contracting by the compensation price**.** Own representation based on Berger and Bierwirth, 2009, p. 631.

3.4.1. Procedure for the reassignment of requests

In contrast to the central planning approach executed for multi-depot problems (MDTSPPD), decentralized planning relies on absence of information transparency. Hence, the reassignment of requests is executed by a decentralized "autonomous acting agent" (p. 632), which is legitimized by the participating carriers. Nevertheless, the incentive scheme of the auction framework must provide a reliable and efficient environment to obtain the carriers' commiseration.
The process of an auction round can be divided into five steps.
The starting situation is given by the initial distribution of request portfolios held by the carriers $N = N_1 \cup N_2 \cup \ldots \cup N_m$.

According to Berger & Bierwirth an auction round passes through the following steps:

1. *"Forming a request candidate set*: Every carrier $i \in M$ chooses request $j_i \in N_i$ with the lowest marginal profit as a candidate for a possible reassignment. The value p_{ij} is viewed by the carrier as a floor price for request j_i. The set of candidate requests in the network is $S = \{j_1, j_2, \ldots, j_m\}$.
2. *Composition of bundles from the candidate set*: A number of bundles $S_k \subseteq S(k = 1, \ldots, s)$ is selected for the reassignment process. In the simplest case there is only a single bundle containing a single request. In the other extreme all subsets of S define bundles.
3. *Determination of marginal profits*: Every carrier i determines the marginal profit p_{ik} for each bundle S_k of requests, without taking into account the corresponding compensation prices.
4. *Assignment of bundles to the carriers*: The bundles are tentatively assigned to carriers such that the sum of the related marginal profits, computed in in Step 3, is maximized. If a request is contained in multiple bundles, only one of these bundles is assigned to a carrier.
5. *Profit sharing*: If the period profit of the CCN has increased by the reassignment, the profit gain is split up among the concerned carriers. Otherwise, the attempted reassignment of requests failed" (p. 632).

This procedure is repeated iteratively and ends if no more requests of the candidate set can be reassigned. During the auction process all carriers can act as both buyer and seller.

Berger and Bierwirth introduce two kinds of algorithms, which are explained in the following section underlined by an example.

3.4.2. Single Request Reassignment

The explanation of the Single Request Reassignment Algorithm (SRRA) is continued on the example presented in Section 3.3. The actual progress right before the start of the auction is the following: So far, the participating carriers planned the initial tours autonomously and determined the marginal profit of all requests as shown in Table 6. In the following section the reassignment process is presented according to the example and the transaction is drawn in Figure 4.

In *Step 1* the carriers identify the request with the lowest marginal profit. The formed candidate set consists of $S = \{3,4,9\}$.

In *Step 2* the central authority forms the bundle which is relevant for the reassignment. In case of SRRA and BRRA this applies to the request or request bundle with the lowest marginal profit of the candidate set. It can be assumed that a request with low marginal profit tends to be advantageous for a reassignment.

In S*tep 3* Carrier 1 owns the request with the lowest marginal profit and acts in this round as the auctioneer. The auctioneer's marginal profit serves as the floor price with 9,1 in the ongoing auction round. Then Carrier 2 and 3 evaluate the marginal profit of the surveyed request by including it in their operational planning scheme. As a result, the potential gain for carrier 2 is 25 and for carrier 3 it is 37.[4] These prospective marginal profits serve as bidding prices.

In *Step 4* the carrier with the highest bid is identified. In this case Carrier 3 is the highest bidder. Based on the Vickrey auction structure, the second highest bid serves as the compensation price. If only one bid is above the floor price, this bid is treated as the compensation price. If no bid exceeds the floor price, the auction fails at this point. Then the procedure is repeated at Step 2 and another request of the candidate set takes part in the auction.

Finally in *Step 5* the potential network outcome is evaluated: here in respect to the compensation price offered by Carrier 2, the profit gain for Carrier 1 is $\Delta P_1 = 25 - 9$ and the profit gain for Carrier 3 is $\Delta P_3 = 37 - 25$. As a result, the total network profit is

[4] For illustrative purposes, these values of the example deviate from the original output.

positive (16+12) and the reassignment can be realized. That is, request 3 leaves set N_1 and enters the portfolio of N_3. Subsequently, a new iteration starts with Step 1 by building a new candidate set. Assuming that the delta profit is negative, the reassignment of the surveyed request is rejected and a not yet considered request from the candidate set is chosen. The auction process terminates if all requests of the current candidate set do not further increase the network profit.

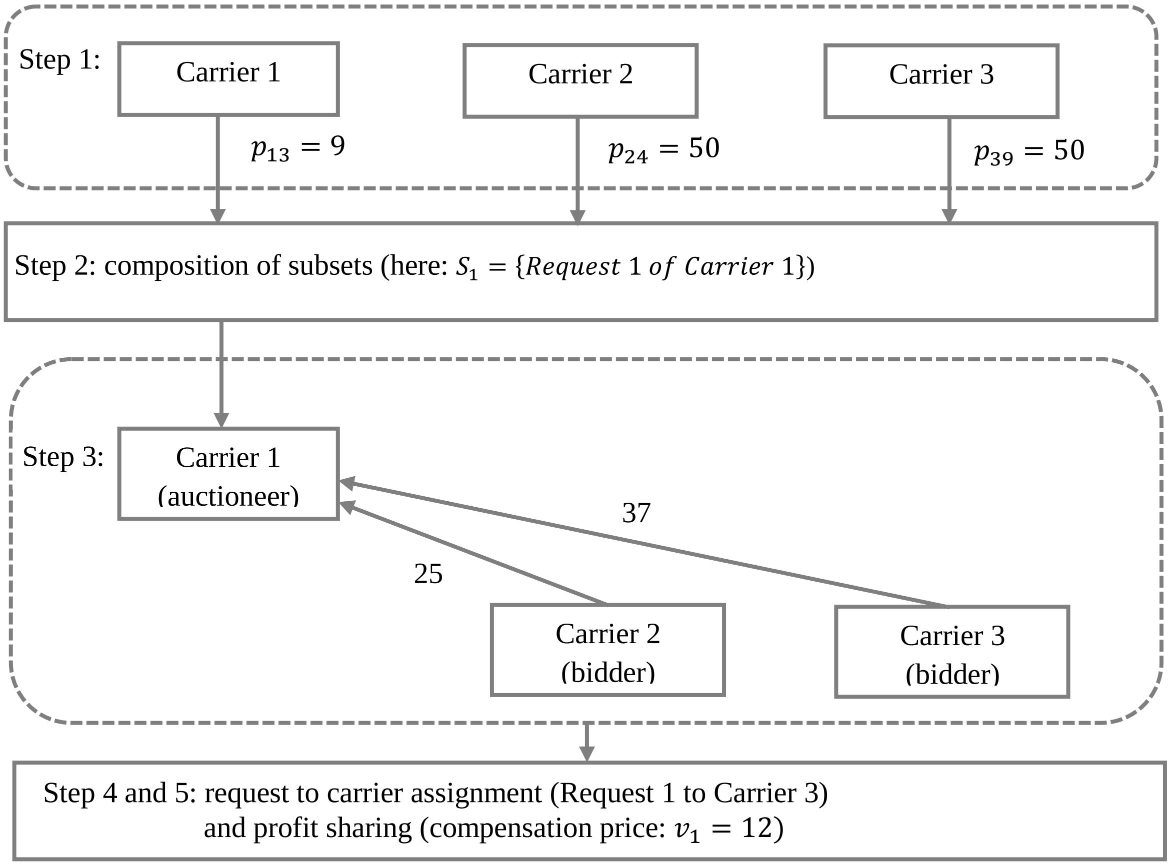

Figure 4: Sketch of a single request reassignment. Own representation based on Berger and Bierwirth, 2009, p. 634.

3.4.3. Bundle Request Reassignment

The economic efficiency of an auction procedure can be enhanced by respecting bundling effects. For this reason Berger and Bierwirth compiled the Bundle Request Reassignment Algorithm (BRRA) to advance the collaboration's efficiency.

Therefore, in Step 2 all possible subsets of bundles from the candidate set are considered. To enable bidding activities on request bundles, Berger and Bierwirth implement a combinatorial auction. The winner of the combinatorial auction is determined by solving the Combinatorial Auction Problem (CAP). According to Berger and Bierwirth, the problem is defined in the following way: “Let M denote a set of bidders (carriers), S a set of m items […], and $b_i(S_k)$ the bid that bidder $i \in M$ is willing to pay for bundle $S_k \subseteq S$. Furthermore, let $y(S_k, i)$ denote a binary decision variable indicating whether S_k is allocated to $i \in M$ or not” (p. 634). The objective of the CAP is to maximize the cash flow of the auction. Similar to the SRRA, the bids are represented by the marginal profits a carrier can obtain for servicing a bundle of requests. Hence, solving the CAP maximizes the network profit after the reassignment of a bundle of requests. The CAP is formulated by Berger and Bierwirth as follows:

$$Z = \sum_{i \in M} \sum_{S_k \subseteq S} b_i(S_k) \cdot y(S_k, i)$$
$$1 \geq \sum_{i \in M} \sum_{S_k \ni j} y\,(S_k, i) \qquad (\forall j \in S)$$
$$1 \geq \sum_{S_k \subseteq S} y(S_k, i) \qquad (\forall i \in M)$$
$$y(S_k, i) \in \{0,1\} \qquad (\forall S_k \subseteq S, i \in M)$$

In the following, the five step procedure executing BRRA is demonstrated in form of an example:

In Step 1 the Bundle Request Reassignment Algorithm forms the candidate set similar to the SRRA with $S = \{3,4,9\}$.

In contrast to the SRRA, in *Step 2* all possible subsets of the candidate set S are composed, leading to seven bundles $S_1 = \{3\}$, $S_2 = \{4\}$, $S_3 = \{9\}$, $S_4 = \{3,4\}$, $S_5 = \{3,9\}$, $S_6 = \{4,9\}$ and $S_7 = \{3,4,9\}$.

In *Step 3* the carriers incorporate each bundle to their operational planning instance to determine their marginal profit. These values are communicated to the central authority and inserted in a bid matrix.

$$[b_i(S_k)] = \begin{bmatrix} b_1(S_1) & \dots & b_1(S_k) \\ \vdots & \ddots & \vdots \\ b_m(S_1) & \dots & b_m(S_k) \end{bmatrix} = \begin{bmatrix} 9 & 67 & 52 & 75 & 60 & \mathbf{126} & 126 \\ 3 & 50 & 35 & 59 & 43 & 76 & 84 \\ \mathbf{5} & 40 & 51 & 48 & 58 & 94 & 101 \end{bmatrix}$$

After solving the CAP, the combination of $b_1(S6) = 126$ and $b_3(S_1) = 5$ produces the highest possible cash flow. As an outcome, Carrier 1 acquires the requests of Carrier 2 and 3 and sells its request to Carrier 3. The evaluation of the network profit is derived by the total cash-flows which are “reduced by the bids that the carriers have announced for their own requests (representing the floor prices)" (p. 635). In this case, the post-reassignment profit is positive $\Delta P = 126 + 5 - (9 + 50 + 51)$ and the reassignment is realized.

For information about the internal profit sharing calculations which do not impact the objective function of the model, I refer to the demonstrations depicted by Berger and Bierwirth.

3.5. Model formulation of the CCRP

The optimization problem of the CCN consists in finding the maximized total profit of the CCN by reassigning requests to carriers, under the consideration that the carriers achieve an optimal route for their vehicles. "A transfer of request j from carrier i to carrier k is represented in the framework by j leaving N_i and entering N_k" (p.631). For In order to identify the role of a carrier in the reassignment process and the appendent profit computation, the authors introduce a binary variable x_{ij} whether $j \in N$ is served by $i \in M$ ($x_{ij} = 1$) or not ($x_{ij} = 0$). Therefore, the profit evaluation scheme is extended where carrier i determines the marginal profit of a request $j \in N$ in the following way:

$$p_{ij} = \begin{cases} (r_j - c_{ij}) \cdot x_{ij} + v_j \cdot (1 - x_{ij}), & \text{if } j \in N_i, \\ (r_j - c_{ij} - v_j) \cdot x_{ij}, & \text{otherwise.} \end{cases} \tag{9}$$

Here, r_j and c_{ij} are computed according to (1) and (3). In case carrier i acts in form of self-fulfillment ($j = N_i$ and $x_{ij} = 1$), the formula corresponds to the original profit calculation like in equation (6). In case that carrier i has contracted request j in the first place and later on decides to sub-contract it again, the marginal profit of carrier i is denoted by the compensation price v_j paid by carrier k. Finally, if carrier i appears as sub-contractor itself ($j \notin N_i$, and $x_{ij} = 1$), the profit margin emerges from the revenue and costs servicing the request minus the paid compensation price v_j.

Consequentially, the objective of the CCN "is to reassign requests to carriers with respect to the paid compensation prices such that the period profit is maximized" (p.631), leading to the model formulation of the CCRP:

$$\max \quad P = \sum_{j \in N_i} r_j - \sum_{i \in M} C_i \tag{10}$$

$$\text{s.t.} \quad 1 = \sum_{i \in M} x_{ij} \quad (\forall j \in N) \tag{11}$$

$$C_i = \sum_{j \in N} \beta_1 x_{ij} + L(\{j \in N | x_{ij} = 1\})\beta_2 \quad (\forall i \in M) \tag{12}$$

$$P_i^0 \leq \sum_{j \in N} r_j x_{ij} + \sum_{j \in N_i} v_j(1 - x_{ij}) - \sum_{j \in N \setminus N_i} v_j \, x_{ij} - C_i \quad (\forall j \in N) \tag{13}$$

$$x_{ij} \in \{0,1\} \quad \text{and} \quad v_j \in \mathbb{R} \quad (\forall i \in M . \forall j \in N) \tag{14}$$

The objective function (10) maximizes all revenues gained from the requests minus the total costs of all carriers. Since the total revenue is constant, it is also possible to minimize the total costs solely. Equation (11) states that every request is assigned to exactly one carrier. The transportation costs for each carrier are computed in constraint (12) where solving the TSPPD (to optimality) is included by $L(\cdot)$. Constraint (13) ensures that the carrier's profit cannot deteriorate after reassigning a request to another carrier.[5] An important observation mentioned by Berger and Bierwirth is that the compensation prices are decision variables, but they do not appear in the objective function because they are reflected only as internal transfer prices.

[5] Furthermore Berger and Bierwirth remove a non-linearity in equation (13).

3.6. Instance characterization

The problem sets created by Berger and Bierwirth are based on the instance of Solomon R101 (Solomon, 2005). The 101 locations are plotted in Figure 5. The depots of the three carriers are located at city 10, 54 and 93. Furthermore Berger and Bierwirth established three instance sets which indicate a differentiated degree of competition between the carriers.

The authors divide the whole area into three disjoint subsets X_1, X_2 and X_3, separated by the continuously drawn lines. Berger and Bierwirth distinguish between adjacent, overlapping and identical customer areas and generate three instance sets A,O and I. For each layout, 30 instances are drawn randomly, according to following rules: In Set A Carrier i only receives customers from sub-set X_i. For Set O with overlapping customer areas, each carrier may receive additional cities from the area inside the dashed triangle. In Set I with identical customer areas, all nodes are available for a carrier's initial customer portfolio.

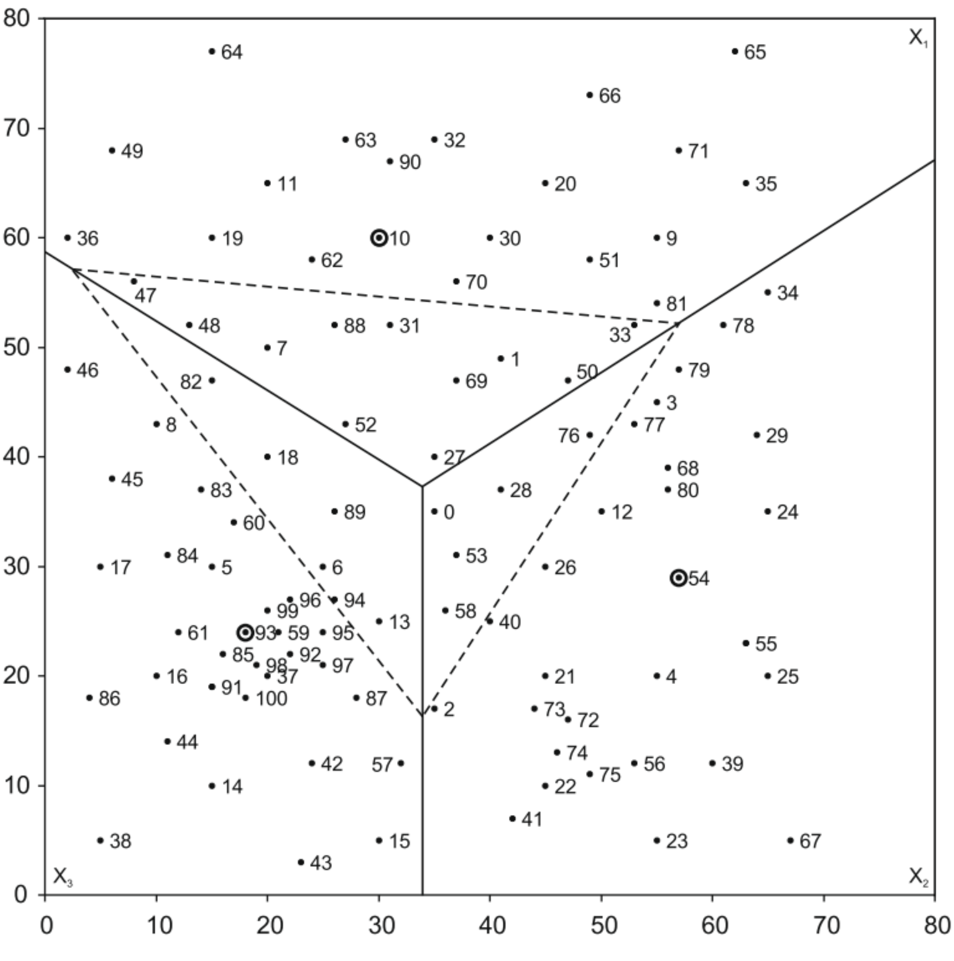

Figure 5: Instances generated according to Solomon R101. Figure by Berger and Bierwirth, 2009.

4. An alternative implementation of the CCRP with a heuristic tour building algorithm

The design of this implementation bases on the CCN designed by Berger and Bierwirth. The relevant modification of my approach in comparison to the work of Berger and Bierwirth appears in the tour building procedure: In order to determine the marginal profits of requests and building tours, Berger and Bierwirth solve the TSPDP at all points to optimality while in the alternative implementation the transportation problem is solved heuristically. The authors solve the TSPPD by a branch and cut algorithm of Dumitrescu et al. (2007). The tour algorithm applied in this thesis solves the TSPPD according to Renaud et al. (2000): "*A heuristic for the pickup and delivery traveling salesman problem*".

Berger and Bierwirth invented the theoretical model and solved it in a quantitative manner to prove the benefits of a carrier collaboration network design. On the one hand side, my research question addresses the problem how the reassignment of transportation requests is affected by applying heuristics for the tour building process instead of tours solved to optimality. On the other hand, the model design of Berger and Bierwirth is extended in three different ways in aspiration to increase the network profit. Furthermore the appliance of a heuristic tour building procedure gives the opportunity to solve the problem with instances which involve more than the 18 customer locations in the standardized version. Hence, the results are analyzed and discussed in regard to Berger and Bierwirth.

4.1. Method for solving the TSPPD

The chosen method for solving the TSPPD is based on the work of Renaud et al. (2000). This heuristic for solving the transportation problem was selected because the authors derive very good results with comparably short running times. It is composed of a solution construction phase applying a "Double Insertion Heuristic" and followed by an improvement phase performing a local optimization in terms of a 3-opt algorithm.

The transportation problem is defined according to Renaud et al. (2002) as following: An undirected graph $G = (V, E)$ with a vertex set $V = \{v_1, \dots, v_n\}$, indicating that n is an odd number, v_1 denotes the depot and $E = \{(v_i, v_j): i < j, v_i, v_j \in V\}$ represents the edge set. The set $V\backslash\{v_1\}$ is composed into $\{P, D\}$, where P denotes a set of pickup customers and D is a set of delivery customers. The size of the two sets is the result from $|P| = |D| = (n-1)/2$. "These two sets are twinned in the sense that to each pickup customer, $v_i \in P$ corresponds exactly one delivery customer $d(v_i) \in D$, and to each delivery customer corresponds exactly one pickup customer" (Renaud et al., 2002, p. 1130). An Euclidean distance matrix $C = (c_{ij})$ is defined on E.

4.1.1. Construction Phase: Double Insertion Heuristic (DI)

In the initialization phase, the vertex pair $v_{i^*}, v_{j^*} = d(v_{i^*})$ leading to the longest possible tour $max_{v_i \in P}\{c_{1i} + c_{ij} + c_{j1}\}$ is identified. In the subsequent steps, the remaining pairs $(v_i, d(v_i))$ are included sequentially into two score functions and the pair achieving the lowest score value is inserted.

Case 1: Not yet surveyed vertex pairs consisting of v_{i^*} and v_{j^*} are inserted consecutively between vertices v_k and v_l. The set of edges in the current sub-tour is indicated by F. Score 1 is constituted as:

$$SCORE\ 1 = \min_{v_i \in P, (v_k, v_l) \in F} \{\delta c_{ki} + c_{ij} + (2-\delta)c_{jl} - c_{kl}\}$$

with δ as a user-controlled parameter ($0 \leq \delta \leq 2$).

To further illustrate the Double Insertion Heuristic, an example is drawn in Figure 6. In an actual tour, one order-pair (circles) is already inserted in the tour according to the initialization phase. At this stage, a vertex pair v_{i^*} and v_{j^*} (triangle) is inserted in three different ways:

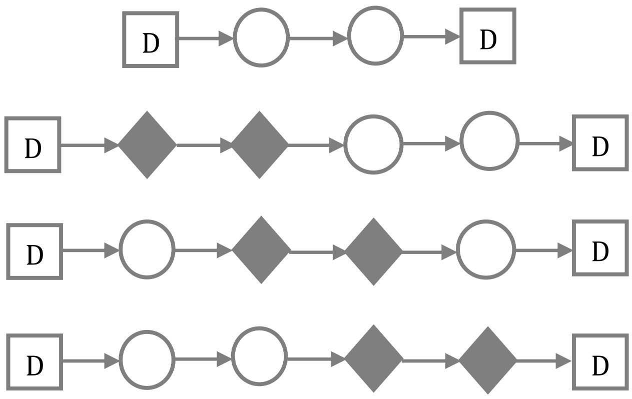

Figure 6: Score 1: possibilities of inserting a vertex pair in a current tour which implies actually one request

Case 2: A vertex pair v_{i^*} and v_{j^*} is inserted in between vertices v_k, v_l and v_r, v_s, "respectively, where (v_r, v_s) appears after (v_k, v_l) on the sub-tour." (Renaud et al, 2002, p. 1132). Then Score 2 function is defined as:

$$SCORE\ 2 = \min_{v_i \in P, (v_k, v_l), (v_r, v_s) \in F} \{\delta(c_{ki} + c_{il} - c_{kl}) + (2 - \delta)(c_{rj} + c_{js} - c_{rs})\}$$

After all remaining vertex pairs have passed through both score functions, the pair $(v_{i^*}, d(v_{i^*}))$ yielding to the lowest score value "is then inserted in its appropriate position in the sub-tour $P \coloneqq P \backslash \{v_{i^*}\}$" (Renaud et al., 2002, p.1132). Score 2 is exemplified in Figure 7.

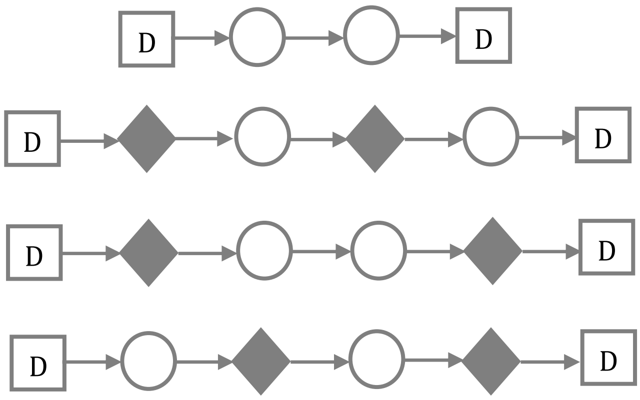

Figure 7: Score 2: possibilities of inserting a vertex pair in a current tour which implies actually one request

The insertion procedure terminates when all vertices are included in the current tour. After severe testing, the authors determined the constant $\delta = 1{,}25$. In this work, the outcome is derived for $\alpha = 1{,}25$.

4.1.2. Improvement Phase: 3-opt optimization

The 3-opt TSP improvement heuristic proposed by Lin (1965) is a local search procedure. Hereby, three edges are selected and the connections between them are destroyed. Then the edges are reconnected in eight possible combinations as illustrated in Figure 8. In case of solving a usual TSP by means of 3-opt, "each single exchange takes constant time but for the TSPPD each exchange may take an amount of time proportional to […] the total number of vertices" (Renaud, Boctor, & Quenniche, 2000, p. 908). That is due to checking the feasibility of the precedence condition after each iteration. Hence, the run-time complexity for each iteration increases from $O(n^3)$ to $O(n^4)$.

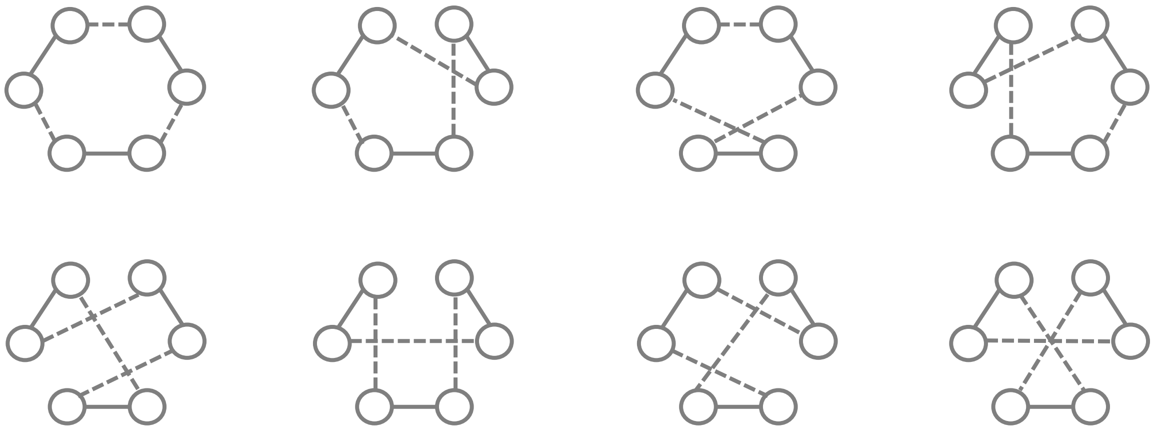

Figure 8: All possible 3-opt combinations. Representation based on Blazinskas & Misevicius, 2010, p. 2

4.1.3. Solution quality of applied heuristics

The benchmarks are retained from Renaud et al. (2000). They derived in total 108 problem instances with up to 441 vertices handling the TSPPD with precedence constraints. The average percentage increase of all instances in comparison to the optimal solutions is reported for the Double Insertion heuristic applied solely with 12,20%. Including the 3-opt optimization, the average percentage aberration improves to 3,87% against the optimal solution.

4.2. Format of results

Berger and Bierwirth derived several types of results depending on the degree of information transparency. Therefore, they setup three strategies:

a. No market information is shared between the freight forwarding companies.
b. The information between the collaborators is shared to a certain extent.
c. All information is accessible for the participating carriers.

The initial result indicated by (a) is the network profit with no collaboration P_{nc}, which measures the profit generated by the carriers autonomously. In contrast, P_{cp} denotes the network profit gained by solving the MDTSPPD. This central planning approach (c) states the optimal solution for the network. In the decentralized planning strategy (b), the carriers handle either information concerning one single request or the data contained in a bundle of requests. Assuming that the network profit increases with a rising information transfer, in case of BRRA the portion of shared information is higher. So the authors conclude that the network profit of bundle reassignments P_{br} exceeds the outcome of single reassignments P_{sr}. Thereupon Berger and Bierwirth deduce that $P_{nc} \leq P_{sr} \leq P_{br} \leq P_{cp}$ should hold. Furthermore the authors introduce two performance indicators: Firstly "the collaboration gain $\theta = \frac{P-P_{nc}}{P_{nc}}$ measures the relative gap of the network profit P for a strategy against the profit achievable without collaboration" (p.635). Secondly the decentralization cost $\varphi = \frac{P_{cp}-P}{P_{cp}}$, examining the profit loss of decentralized planning against the central planning approach.

4.3. Computational results of standardized settings

In the presentation of the computational results, the model of Berger and Bierwirth is treated as the exactly solved version, according to the mode of solving the underlying transportation problem to optimality. In contrast, the alternative implementation is denominated as the heuristic approach. The results of Berger and Bierwirth incur rounding errors due to their exact algorithm works with integer values only. Hence, in the further discussion, results are treated as equal if values do not exceed a two percent range.

4.3.1. Impact of applying heuristics in tour building process

First of all the solution quality of the applied heuristic is examined. Therefore, the network profit without collaboration P_{nc} serves as an indicator compared to the analogical results of Berger and Bierwirth $P_{nc}\ BB$.

The solution quality of the applied heuristic proves as very efficient in regard to the exact solution procedure established by Berger and Bierwirth. Only in six out of 90 instances the heuristics are not able to score the network profits without collaboration $P_{nc}\ BB$ obtained by Berger and Bierwirth. Table 7 shows the deviation induced by the heuristics

based on the average network profit yield without collaboration. Obviously, the aberration is larger for instances with high competition because the average tour length is longer and errors in the tour building stage consign an increased impact.
Consequentially the heuristic version performs slightly worse than the exact solutions. Furthermore, it can be assumed that with a higher degree of competition an increased number of tour building iterations entails the number of auction rounds which leads to more deviating results.

Set A	Set O	Set I	Total
0,46%	0,58%	0,66%	0,57%

Table 7: Standard abbreviation of the network profits obtained by no collaboration $\boldsymbol{P_{nc}}$ in comparison to the network profits with no collaboration $\boldsymbol{P_{nc}\ BB}$ by Berger and Bierwirth

4.3.2. Comparison of results of exact and heuristic approach

In this section, the total network profits for each instance of the occurring problem sets A,O and I are presented in Table 8. The presented solutions show the network from Berger and Bierwirth and respectively the solutions of the alternative implementation in the white columns. In order to visualize differences in the solution outcome between the network profits obtained by Berger and Bierwirth and the alternative implementation, the figures for the alternative implementation are marked in three colours: black discloses equal results, red figures indicate a lower network profit and green values denote a higher network profit derived by the heuristic implementation. The collaboration gain θ and the loss due to decentralization φ are depicted in Table 9.

Set A	P_{nc} BB	P_{nc}	P_{sr} BB	P_{sr}	P_{br} BB	P_{br}	P_{cp} BB
1	21	20	21	20	21	20	25
2	164	164	164	164	164	164	216
3	210	211	210	211	210	211	253
4	187	184	187	184	187	184	187
5	112	112	149	149	149	149	149
6	141	140	190	145	190	145	209
7	237	232	237	232	237	233	300
8	218	220	218	220	218	220	229
9	119	118	142	142	142	142	159
10	230	232	230	232	230	232	289
11	182	179	182	179	182	179	201
12	141	139	141	139	141	139	184
13	156	154	156	154	156	154	172
14	105	105	105	105	105	105	105
15	203	204	203	204	203	203	203
16	208	209	208	208	208	208	243
17	156	153	156	153	156	153	176
18	109	106	109	106	109	106	117
19	171	171	182	182	182	182	202
20	164	164	164	164	164	164	191
21	118	118	119	120	119	120	141
22	167	166	178	179	178	179	209
23	140	142	140	142	140	142	143
24	119	117	121	121	121	121	131
25	182	181	182	181	182	181	220
26	176	178	176	178	176	178	255
27	155	154	157	158	157	158	201
28	203	201	203	201	203	201	225
29	162	162	162	162	162	162	193
30	169	168	169	168	169	168	209

Set O	P_{nc} BB	P_{nc}	P_{sr} BB	P_{sr}	P_{br} BB	P_{br}	P_{cp} BB
31	273	269	273	269	273	269	323
32	121	118	187	158	187	173	236
33	107	105	164	159	164	159	231
34	138	138	247	195	294	236	303
35	167	167	226	229	231	229	282
36	198	197	198	197	198	197	280
37	176	173	176	173	176	173	240
38	213	212	213	213	213	213	340
39	66	63	137	115	169	115	183
40	139	136	184	183	184	183	286
41	209	203	211	207	211	207	269
42	253	256	282	285	282	285	385
43	201	197	222	218	222	218	236
44	215	214	257	257	257	257	360
45	160	160	212	197	212	209	244
46	186	188	241	242	241	242	325
47	161	161	228	226	228	226	294
48	162	161	173	171	199	197	230
49	123	122	155	148	172	172	211
50	241	240	241	240	241	240	311
51	160	160	255	211	212	214	319
52	219	219	280	221	300	221	300
53	87	87	114	112	114	112	143
54	165	167	237	237	237	237	307
55	158	157	210	207	205	207	286
56	155	153	229	193	229	196	286
57	303	302	349	331	349	348	452
58	232	233	303	255	255	255	385
59	344	342	344	342	344	342	465
60	288	288	378	318	378	318	463

Set I	P_{nc} BB	P_{nc}	P_{sr} BB	P_{sr}	P_{br} BB	P_{br}	P_{cp} BB
61	139	140	263	214	320	230	320
62	102	100	272	231	187	165	373
63	142	142	265	177	265	177	367
64	91	91	158	143	158	143	227
65	176	176	189	188	189	188	403
66	141	141	307	308	378	320	439
67	283	283	283	283	283	283	491
68	234	236	288	289	417	405	483
69	170	170	259	237	258	215	355
70	202	203	314	304	237	259	398
71	158	159	332	267	382	343	478
72	84	83	128	264	168	272	346
73	171	173	228	232	228	236	430
74	303	302	303	320	327	450	553
75	163	161	366	346	464	346	464
76	343	342	458	441	573	468	573
77	210	209	338	284	338	284	427
78	224	224	289	253	363	290	440
79	164	151	307	243	408	243	413
80	239	240	414	357	418	384	533
81	61	62	61	162	302	192	302
82	52	52	185	181	293	91	314
83	253	251	559	383	582	449	582
84	203	203	358	327	403	327	453
85	237	238	492	379	492	350	520
86	281	282	465	395	465	395	500
87	185	162	406	225	406	225	487
88	312	311	331	373	482	373	585
89	340	337	459	369	459	369	541
90	256	256	527	363	527	377	527

Table 8: Network profits of the three instance sets A,O and I. Grey columns contain results of Berger and Bierwirth (BB). White columns represent network profits of the alternative implementation. Results are treated as equal if values do not exceed a two percent range. P_{nc}: Network profit without collaboration. P_{sr} or P_{br}: Network profit applying SRRA or BRRA. P_{cp}: Network profit of central planning approach.

Set	Collaboration gain θ MDTSPPD	P_{sr} BB	P_{sr}	P_{br} BB	P_{br}	Loss due to decentralization φ P_{sr} BB	P_{sr}	P_{br} BB	P_{br}
A	19,0	3,5	2,7	4,7	2,7	12,6	13,7	12,5	13,7
O	67,4	28,7	21,3	30,8	24,5	22,7	27,2	22,0	25,5
I	155,7	76,6	63,1	100,9	64,2	27,3	36,3	21,9	34,8

Table 9: Collaboration gain $\boldsymbol{\theta}$ and loss due to decentralization $\boldsymbol{\varphi}$ in percent.

4.3.3. Instance Set A without competition

The initial solution P_{nc} can be improved by the central planning approach with a collaboration gain θ of 19%. The decentralized planning strategies SRRA and BRRA by Berger and Bierwirth lead to a collaboration gain θ of 3,5% and 4,7%, whereby an improvement occurs only in eight instances. In six out of eight cases the heuristic version achieves the identical improvements leading to an overall collaboration gain φ of 2,7%. The heuristic version falls short in instance #7 and #18, otherwise the improvement due to collaboration is equal.

4.3.4. Instance Set O without competition

In Set O with overlapping customer locations the enhancements by collaboration become more apparent. The exact results of Berger and Bierwirth score betterments in 24 out of 30 instances with a collaboration gain θ of 29% for SRRA and 31% for BRRA. The heuristically solved method acts similar and leaves an interesting mark: In case the network profit of an instance can be enhanced by decentralized collaboration initiated by Berger and Bierwirth, the heuristic model always achieves a profit shift in this surveyed instance as well. However, the same profit outcome is attained only in 11 out of 24 instances, leading to a lowered collaboration gain θ of 21% for SRRA and 24% for BRRA.

4.3.5. Instance Set I without competition

As assumed, the picture changes profoundly for the instance Set I with a high degree of competition. The results between the exact and heuristic approach differ distinctly. For the single reassignment method the network profit coincides with five instances only, but even achieves a higher network profit at four instances. The network outcome for BRRA deviates even more. Expressed by the collaboration gain θ, the improvements of Berger and Bierwirth are given for SRRA with 77% and for BRRA with 100%. The heuristic performance only accomplishes a collaboration gain of 63% for SRRA and 64% for BRRA.

4.3.6. General Observations

At first, the behavior of the reassignment algorithms SRRA and BRRA is examined: In the alternative implementation, BRRA performs in instance sets with no and middle competition at least as good as SRRA. In a market with high competition, SRRA dominates BRRA in a some instances (#62, #69, #70, #82, #85). In a similar constellation, these events appear in the outcome of Berger and Bierwirth. They bring forward the argument that an auction can be seen as a repetitive procedure, wherein SRRA and BRRA process local search moves in a neighboring solution until a local optima is reached. Hereby the solution space of BRRA is bigger which is likely to lead to a better solution. “However, by chance SRRA can follow a more favorable search trajectory than BRRA leading into an area of the search space where better solutions are located” (p.636). Hence, SRRA and BRRA both are heuristics among which BRRA is the more promising approach.

Furthermore the auction outcome in the model of Berger and Bierwirth can be disturbed due to rounding errors. Assuming such a rounding error leads to a false evaluation of a request’s marginal profit, an execution of an auction could be rejected or a disadvantageous request could be reassigned guiding into a different solution space. Such a scenario probably worsens the solution quality, but it is also possible that in a continued process a preferable neighborhood is entered, leading to a higher network profit.

Recapitulating the situation in Set I where the alternative implementation exceeds the network profit in comparison to the model of Berger and Bierwirth, (#70-74, #81, #88) the outcome of Berger and Bierwirth acts considerably below the average performance.

For example, looking at instance #81, the network profit does not evolve for SRRA, but boosts up by almost 400% by applying BRRA. At this point, it can be assumed for the implementation of Berger and Bierwirth that for executing SRRA an auction failure occurs due to rounding errors. On the other hand, in the alternative implementation there is a chance that during the heuristic tour building process applying SRRA, in an early auction iteration an adverse request is chosen for a reassignment which leads to an advantageous solution.

Regarding the loss of decentralization the results of Berger and Bierwirth and the alternative approach behave similar for instance sets with low and medium competition. The values are slightly better for the exact method. In the heuristic solved version the loss due to decentralization increases constantly with heightened competition. Noticeably the model of Berger and Bierwirth settles down at 22% percent for BRRA while in the alternative setup the indicator ascends continuously. This behavior is also documented in the superiority of the exactly solved method, achieving in six instances of Set I applying BRRA the same network profit as the centralized planning approach. In contrast, the alternative version is not once able to fully utilize the central planning outcome.

4.3.7. Computational effort

By solving the integrated transportation problem heuristically the running times are notably shorter in the alternative implementation as for the exact solutions provided by Berger and Bierwirth as shown in Table 10. The run times for the alternative implementation are reported on a PC P4 3000 MHz and are measured in seconds. Berger and Bierwirth operated on a similar system.

Set	SRRA		BRRA	
	Berger & Bierwirth	Alt. impl.	Berger & Bierwirth	Alt. impl.
A	0,41	0,07	0,6	0,34
I	11,61	0,34	3,97	0,89

Table 10: Average run times in seconds for solving the instance Sets A and I by Berger and Bierwirth in comparison to the alternative implementation

4.4. Extensions for the model of Berger and Bierwirth

The following extensions applied for the model of Berger and Bierwirth focus on improving the overall network profit. Therefore, three additional extensions are implemented. Furthermore, different combinations of the extensions and setting changes of the enhancements are analyzed. This allows retrieving further information about the model sensitivity of Berger and Bierwirth in regard to changes in the framework.

4.4.1. Considering all Requests in an Auction Iteration (CAR)

In the framework of Berger and Bierwirth an auction iteration permits only the request with the lowest marginal profit of each carrier to be included in the candidate set. In case that the evaluation of the bundle of requests does not lead to a higher network profit in *any* combination, the auction terminates. At this point the alternative implementation permits the auction to continue at Step 1 again. Then each carrier scans for the request yielding the next lowest profit value of a not yet considered request and forwards it to the auction agent. The auction proceeds as usual with Step 2 building the new candidate set. The auction round ends when all carriers offered each request at least once. The implemented process of executing CAR is further exemplified in a flow diagram in Figure 17.

As the current quantity of requests owned by the carriers may vary, there are scenarios in which a carrier already offered all requests while other carriers still hold not yet considered requests. In such cases carriers with fewer customers always offer the request indicating the lowest marginal profit.

A concrete example (instance #37) is illustrated in Figure 9. The initial tours of Carrier 1 and Carrier 2 are shown in the chart on the left. At the first stage Carrier 1 identifies the order composed of P1 and D1 as the request with its lowest marginal profits and Carrier 2 forwards request P4-D4 into the candidate set. Executing SRRA, in the usual auction process a profit gain is achieved neither by Berger and Bierwirth nor by the alternative implementation. Now the program jumps back to Step 1 and places the requests with the second lowest profits into the candidate set, though both order pairs P3-D3 and P5-D5 do not lead to a reassignment. Back at Step 1, the remaining requests P2-D2 and P6-D6 form the candidate set. Hence, the reassignment can be processed and the emerging tours of Carrier 1 and Carrier 2 are illustrated on the right in Figure 9.

The profit gain for the network due to this reassignment is determined in Table 11. The difference between the tour lengths of the initial and the new tour yield to a network profit gain of 47 in instance #37.

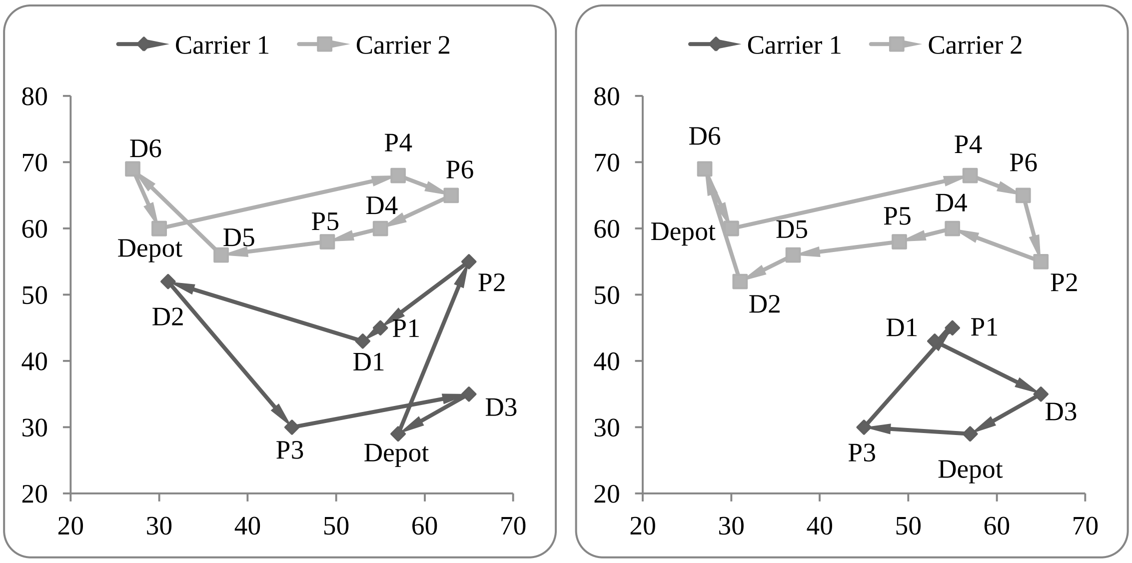

Figure 9: Tours of Carrier 1 and 2 of instance #37. Left: Initial tours. Right: Tours after auction iteration considering all requests in an auction round

	Initial tour length	New tour length
Carrier 1	124,6	57,3
Carrier 2	88,6	108,9
Sum of tour lengths	213,2	166,2
Network gain	47	

Table 11: Initial tour lengths and tour lengths after the auction iteration considering all requests. In addition, the derived network gain due to the reassignment is illustrated. Instance #37 SRRA.

4.4.2. Tolerating the reassignment of requests (TR)

As already stated in Section 3.5 the reassignment activities take part in a daily planning horizon. Berger and Bierwirth explicitly state that a request which is reassigned successfully once, cannot participate in subsequent auction rounds. From a technical point of view, a repetitive reassignment of an already auctioned request is accomplishable and a potential benefit for the collaboration. Assuming a carrier sells a request r_j in an early auction phase and in the further auction process this carrier is involved in additional reassignments, the former request r_j can actually fit into the current request portfolio efficiently.

4.4.3. Revenue Settings for evaluating Requests

In Section 3.3 the evaluation of requests is presented according to Berger and Bierwirth. The assessment for the charge of a request a carrier obtains from a shipper is denoted by a fixed service rate of α_1= 20 and a distance dependent rate between pickup and delivery customer α_2= 2.

These values are chosen reasonably especially in association with the appendent cost calculation. Nevertheless, the evaluation of an order turns out to be unprofitable. In many cases carriers have a bias towards placing requests in the candidate set which are not beneficial in regard to the tour's or respectively the collaboration's efficiency. This is provoked by the appraisal procedure of orders. The revenue of an order-pair dominates the marginal cost of the request which a carrier has to pay for servicing the additional request. For this reason, carriers tend to place requests in the candidate set which provide low revenue rather than requests disturbing a tour's efficiency. Therefore, two alternative settings are examined by adjusting the revenue rates of alpha.

The fixed transportation charge α_1 does not affect the comparative evaluation of requests and is negligible. The rather balanced adjustment is executed with maintaining $\alpha_1 = 20$ and adapting $\alpha_2 = 1$. Now the distance dependent charge between customers equals the travelling cost per kilometer. The extreme case runs with $\alpha_1 = 200$ and $\alpha_2 = 0$ ignoring the relevant charge entirely. In the latter case $\alpha_1 = 200$ obtains a value high enough to ensure a feasible auction outcome.[6] These settings for alpha are only active in the process of determining the marginal profit of requests. In contrast, the calculation of the final network profit still utilizes the original values of alpha. Returning to the example introduced in Section 4.4.1 (instance #37), the determined marginal profit of requests differs decisively, not only in absolute values, but also in the essential relative terms, as depicted in Table 12. With the adapted alpha values the outcome of this auction round is identical to the output as if all marginal requests are considered in an auction iteration. In the original setting, Carrier 1 disposes Request 1, because the order provides the lowest marginal profit (9,0) of its request portfolio. By modifying the alpha settings, Request 2 is yielding the lowest marginal profits in both cases. As already illustrated in Figure 9, Carrier 1 sells Request 2 to Carrier 2 leading to an improvement of the network profit.

Carrier 1				Carrier 2			
Request	$\alpha_2 = 2$	$\alpha_2 = 1$	$\alpha_2 = 0$	Request	$\alpha_2 = 2$	$\alpha_2 = 1$	$\alpha_2 = 0$
1	9,0	6,2	183,3	4	24,9	16,6	188,4
2	10,9	-23,2	122,7	5	28,9	16,7	184,5
3	29,3	8,6	168,0	6	56,7	20,5	164,2

Table 12: Marginal profits of requests for Carrier 1 and Carrier 2 applying different settings for alpha: initial revenue setting: $\boldsymbol{\alpha_2 = 2}$**;** moderate settings: $\boldsymbol{\alpha_2 = 1}$**;** distinct setting**:** $\boldsymbol{\alpha_2 = 0}$. Values retrieved from Instance #37.

4.5. Computational results considering the extensions

In the following section, the network profits attained by the extensions are compared to the results of Berger and Bierwirth and to the initial outcome of the alternative version. The additional benchmarks utilized in the further analysis are characterized as follows:

Abbreviation	Description
$\alpha_2 = 1$ & $\alpha_2 = 0$	The revenue charges for evaluating the marginal cost of a request are parameterized with $\alpha_1 = 20$ and $\alpha_2 = 1$ or respectively $\alpha_1 = 200$ and $\alpha_2 = 0$
CAR	Considering All Requests: In an auction iteration all requests are considered
TR	Tolerate Reassignment: Auction tolerates the reassignment of already auctioned requests

Table 13: Explanation of abbreviations applied for the presentation of results

[6] In case the fixed transportation rate α_1 is too low, the delta profit evaluation in Step 5 of the auction procedure would be negative in most instances and reject any reassignments.

The extensions introduced above can be combined with each other. This advancement provides further synergetic effects increasing the network profit. The combination of these approaches is labeled by the use of an ampersand. The collaboration gain θ and the loss due to decentralization φ are presented for the extensions and the reference values $P_{sr}BB$ and P_{sr} in Table 14 and Table 15.

SRRA / **Set**	P_{sr} **BB**	P_{sr}	**TR**	α_2**=1**	α_2**=0**	**TR &** α_2**=1**	**CAR**	**CAR & TR**	**CAR &** α_2 **= 1**	**CAR &** α_2 **= 0**	**CAR & TR &** α_2 **= 1**
A	3,5	2,7	2,6	2,6	2,8	2,6	3,1	3,1	3,2	3,2	3,2
O	28,7	21,3	20,4	28,7	29,6	27,9	28,3	30,3	31,4	30,7	33,0
I	76,6	63,1	48,2	79,3	80,2	68,4	77,3	84,7	84,6	85,2	86,9
BRRA / **Set**	P_{br} **BB**	P_{br}									
A	4,7	2,7	2,8	1,8	2,7	1,8	3,1	3,1	2,3	3,2	2,3
O	30,8	24,5	22,3	26,7	33,3	26,4	30,3	30,1	30,9	33,8	32,3
I	100,9	64,7	52,8	80,4	85,4	75,6	74,8	80,7	83,5	85,9	88,2

Table 14: Collaboration gain $\boldsymbol{\theta}$ in percent of all approaches for the instance sets A,O and I. Top section displays results of SRRA and bottom section results of BRRA.

SRRA / **Set**	P_{sr} **BB**	P_{sr}	**TR**	α_2**=1**	α_2**=0**	**TR &** α_2**=1**	**CAR**	**CAR & TR**	**CAR &** α_2 **= 1**	**CAR &** α_2 **= 0**	**CAR & TR &** α_2 **= 1**
A	12,6	13,7	13,7	13,6	13,5	13,6	13,3	13,3	13,2	13,2	13,2
O	22,7	27,3	27,7	23,1	22,6	23,6	23,4	22,4	21,6	21,9	20,8
I	27,4	36,3	39,4	30,0	29,0	32,8	30,0	27,6	27,9	27,6	26,9
BRRA / **Set**	P_{br} **BB**	P_{br}									
A	12,6	13,7	13,5	14,3	13,5	14,3	13,3	13,3	13,9	13,2	13,9
O	22,0	25,5	26,6	24,1	20,6	24,3	22,0	22,2	21,9	20,4	21,2
I	21,9	34,8	37,8	28,5	27,1	29,6	29,8	27,7	27,2	26,9	25,7

Table 15: Loss due to decentralized planning of all approaches for the instance sets A,O and I. Top section displays results of SRRA and bottom section results of BRRA.

4.5.1. Solution quality for different degree of competition

In case of low competition (Set A) between the carriers, the improvements provided by the extensions appear just slightly. A reasonable explanation is provided by the comparatively low values of loss due to decentralization φ, as shown in Table 15 by the figures P_{sr} and P_{br} yielding both 13,7%. Recognizable betterments only occur in combinations where all requests are considered during an auction round, and the collaboration gain φ raises over 3% for this test series. Mentionable is a decreasing collaboration gain φ for applying $\alpha_2 = 1$ when BRRA is executed.

Looking at the more meaningful configuration with middle and high competition, significant improvements are derived by the use of the introduced extensions. Generally, the applied extensions accomplish similar network profits as Berger and Bierwirth or even exceed the profits looking at the average collaboration gain illustrated in Table 14. Only in one test setting, the extensions of the alternative implementation fall short, this occurs in case for the instance set with high competition executing BRRA.

4.5.2. Tolerate the reassignment of requests (TR)

The auction setting allowing the reassignment of already auctioned requests proves as counterproductive if TR is executed without CAR. The average collaboration gain is in most cases slightly lower than the initial network profit P_{sr} forbidding such reassignments. Apparently, there is no reasonable explanation except to suppose the possibility of getting into an unfavorable solution space due to a recurring reassignment. By contrast, if TR is combined with CAR, the average collaboration gain increases significantly, for example looking at Set I. For SRRA (BRRA) the collaboration gain for the initial heuristic solution P_{sr} is 63,1% (64,7%). If all requests are considered in an auction round, the collaboration gain raises up to 77,3% (74%) and finally combining CAR and TR the collaboration gain increases up to 84,7% (80,7). Thus, one could assume that with a progressing number of auctions initiated by CAR, a reassignment of an already auctioned request tends to be more beneficial.

4.5.3. Consider all requests in an auction round (CAR)

Granting the auction structure to utilize all requests in an auction round increases the collaboration gain significantly. In case of processing CAR exclusively, the collaboration gains of Berger and Bierwirth $P_{sr}BB$ and $P_{br}BB$ are outperformed in four out of six sets. Merely in the Sets A and I executing BRRA the performance of Berger and Bierwirth is superior. The overall best results are produced for combing CAR with the other extensions, whereby the average collaboration gain increases continuously from *CAR* & $\alpha_2 = 1$ to *CAR &* $\alpha_2 = 0$ to finally *CAR &* $\alpha_2 = 1$ *& TR*.

4.5.4. Change in revenue settings ($\alpha_2 = 1$ and $\alpha_2 = 0$)

The outcome provided by the adaption of the revenue settings is very similar to the results produced by CAR. The collaboration gain is slightly lower than for CAR, but the improvements of particular instances turn out to be very similar as for CAR. This is a very promising result because the change of revenue settings should be preferred to the mode of CAR. On the one hand, the flow of information is lower due to the fact that fewer requests are transferred to the auction agent. On the other hand the run time is shortened because fewer route planning iterations occur. Obviously, the average collaboration gain is higher for the distinct approach $\alpha_2 = 0$, where the distance dependent transportation rate is disregarded completely. Nevertheless, the network profit of setting $\alpha_2 = 1$ exceeds scenario $\alpha_2 = 0$ for example in 12 out of 30 instance of Set I performing SRRA, but usually in a lower extent than the other way round.

4.5.5. Sensitivity of the model

Another very interesting observation is the high sensitivity of the model. In order to illustrate this behavior, the standard deviation of the initial network profit P_{sr} and P_{br} and the network profit of all extensions for one instance are used. Table 16 displays the standard deviations exemplary on the instances #62, #65 and #73 which illustrates a high sensitivity within these instances.

Set O BRRA	P_{br}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1	Std. Dev.
62	168	187	302	249	236	168	295	302	249	247	49,04
65	188	188	265	271	261	312	312	317	272	317	46,25
73	236	232	292	309	347	270	297	292	309	347	37,23

Table 16: Showing the standard deviation based on the initial network profit P_{br} and all examined network profits for three instances of Set I performing BRRA

The average standard deviation of an instance set is depicted in Table 17. As expected, for Set A the standard deviation emerges as very low. Changes of the network profit only occur at a small scale in 5 out of 30 instances and for BRRA in 9 instances. In the instance Set O with medium competition the standard division rises for SRRA (BBRA) to 10,25 (11,80) and in Set I with heightened competition the square root is more than doubled.

Set	Algorithm	Avg. Standard Deviation
A	SRRA	0,55
	BRRA	1,11
O	SRRA	10,25
	BRRA	11,80
I	SRRA	23,43
	BRRA	23,38

Table 17: Average standard deviation based on the initial network profit P_{sr}/P_{br} and all examined network profits

A further remarkable finding in regard to the high sensitivity of the profit outcome depends on the direction the auction progress follows in the solution space. As already mentioned above, it appears seldom that the more sophisticated BRRA cannot achieve the network profit of SRRA because by chance SRRA enters a more beneficial solution space or BRRA an inferior path. Similar occurrences are detected for applying the various extensions. The sensitivity of the model in regard to the varying solution space is demonstrated representatively by instance #62 with high competition executed with SRRA as shown in Table 18.

Number of requests carriers service finally				
Solution method	Carrier 1	Carrier 2	Carrier 3	Profit
$\boldsymbol{P_{nc}}$	3	3	3	100
$\boldsymbol{P_{sr}}$	1	4	4	231
TR	2	3	4	187
$\boldsymbol{\alpha_2}$**=1**	5	2	2	250
$\boldsymbol{\alpha_2}$**=0**	3	1	5	231
TR & $\boldsymbol{\alpha_2}$**=1**	4	1	4	236
CAR	1	2	6	251
CAR & TR	1	7	1	295
CAR & $\boldsymbol{\alpha_2}$**=1**	5	2	2	250
CAR & $\boldsymbol{\alpha_2}$**=0**	5	2	2	250
CAR & TR & $\boldsymbol{\alpha_2}$**=1**	6	2	1	283

Table 18: The network profits and number of requests each carrier possesses after the auction procedure is completed. Example drawn from instance #62 (Set I, SRRA).

In the initial pre-auction process each carrier holds three requests and the utilized network profit without collaboration is 100. Examining the outcome of the various solution methods, apparently the composition of requests is altering profoundly. For example, each carrier is servicing at least six requests once in a certain approach. This phenomenon can be monitored frequently for instances with medium and high competition. Here can be seen the importance of accessing an advantageous solution space indicating also a certain random factor.

Noticeably often the highest network profits are yielded in cases where one or two carriers only fulfill a single request and another carrier services a bulk of requests. As illustrated in Table 18, the mode of *CAR & TR* achieves the highest network profit with Carrier 2 servicing seven requests. This leads to the assumption that an accumulating tour of one carrier cannibalizes smaller tours of other carriers. This statement can be strengthened by the thought that a tour encompassing many customers probably is more capable of integrating additional customers than a small tour. Under such conditions an incentive is given to the forwarders manipulate the auction procedure. With an increasing fund of experience carriers could act selfish according to their preferences, either trying to aggregate as many requests as possible or empty their order portfolio. Therefore, in early auction rounds forwarders place bids respectively offers in a way to gain a possible advantage according to their intention.

4.6. Computational results of instances with an increased number of customers

In this section the outcome of the CCRP is analyzed for self-created instance sets with an increased number of customers. The problem sets provided by Berger and Bierwirth examine instances where in the initial setup three carriers service three requests. Hence, in total nine requests respectively 18 customers are considered. Two kinds of additional problem sets are created according to the instances applied by Berger and Bierwirth. The problem sets are labeled as *I27* and *I45*.

Both sets explore a scenario with heightened competition, that is the carriers serve identical customer areas. In set I27, the three participating carriers serve nine requests in case of no collaboration and in set I45 each carrier holds 15 requests initially. The newly created problem sets are assembled from the randomly drawn instances by Berger and Bierwirth, as shown in Table 19. For example, instance 91 (I27) is composed of the problem sets 61, 71 and 81 from Berger and Bierwirth. For the problem set I45 two additional instances are added column wise, as instance 101 from set I45 includes the identical composition as instance 91 plus the additional data implied of instances 65 and 77.

I27										
New instances	**91**	**92**	**93**	**94**	**95**	**96**	**97**	**98**	**99**	**100**
	61	62	63	64	65	66	67	68	69	70
	71	72	73	74	75	76	77	78	79	80
	81	82	83	84	85	86	87	88	89	90
I45										
New instances	**101**	**102**	**103**	**104**	**105**	**106**	**107**	**108**	**109**	**110**
	65	66	67	68	69	70	71	72	73	74
	75	76	77	78	79	80	81	82	83	84

Table 19: Composition of self-created problem sets formed by the instances of Berger and Bierwirth.

In the subsequent discussion the following data is provided: The network profits are determined for the settings without collaboration and the introduced extensions for the model of Berger and Bierwirth. The data is illustrated for Set I27 at Table 20 and the problem set I45 at Table 21. The collaboration gain θ of the various reassignment methods in regard to the solution with no collaboration is given at Table 22. Exact results in regard to the network profits without collaboration and to the central planning approach solving the MDTSPPD are not available.

Instance	P_{nc}	P_{sr} / P_{br}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
91	1026	1241	1049	1157	1210	1276	1283	1180	1203	1219	1296
		1133	1089	1166	1194	1137	1161	1197	1181	1205	1188
92	898	1077	968	1098	1092	1055	1133	1294	1106	1092	1104
		994	975	1133	1127	1097	1112	1293	1187	1202	1140
93	1360	1371	1371	1420	1510	1478	1471	1549	1538	1513	1616
		1412	1389	1435	1542	1475	1587	1518	1480	1545	1511
94	1161	1231	1220	1256	1408	1245	1289	1330	1322	1408	1354
		1191	1217	1250	1317	1254	1297	1301	1271	1337	1396
95	1282	1319	1319	1501	1566	1366	1555	1590	1550	1566	1575
		1319	1319	1501	1551	1451	1510	1551	1547	1546	1575
96	1463	1589	1550	1629	1705	1603	1673	1691	1651	1705	1688
		1630	1551	1629	1705	1603	1749	1682	1667	1684	1729
97	1281	1286	1286	1435	1385	1435	1442	1481	1490	1533	1490
		1286	1286	1478	1385	1435	1384	1443	1495	1473	1450
98	1436	1594	1546	1640	1632	1600	1621	1691	1648	1637	1608
		1533	1520	1608	1634	1559	1507	1687	1599	1607	1658
99	1246	1315	1315	1317	1461	1301	1415	1433	1513	1466	1513
		1290	1301	1433	1423	1301	1517	1441	1513	1433	1413
100	1401	1635	1460	1543	1602	1543	1635	1616	1716	1627	1682
		1500	1460	1539	1615	1543	1657	1687	1598	1617	1549

Table 20: Network profits applying SRRA and BRRA for self-created instances obtaining 27 requests. Brighter row: SRRA. Darker row of instance: BRRA.

Instance	P_{nc}	P_{sr} / P_{br}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
101	2127	2239	2228	2292	2448	2283	2519	2248	2430	2450	2389
		2241	2247	2286	2493	2260	2474	2412	2412	2486	2292
102	2228	2382	2249	2416	2398	2416	2485	2427	2534	2433	2473
		2249	2249	2314	2461	2314	2396	2486	2449	2475	2437
103	2605	2700	2717	2768	2850	2680	2762	2740	2831	2872	2775
		2700	2700	2733	2827	2734	2807	2686	2803	2886	2873
104	2332	2395	2395	2485	2592	2417	2506	2450	2525	2640	2602
		2434	2394	2462	2530	2412	2481	2567	2473	2567	2439
105	2405	2456	2456	2456	2702	2456	2592	2504	2595	2714	2547
		2457	2457	2457	2723	2457	2619	2457	2689	2672	2498
106	2695	2803	2754	2803	2885	2803	2909	2931	2898	2918	2863
		2813	2762	2863	2913	2799	2942	3042	2964	2937	3008
107	2308	2398	2359	2421	2493	2421	2398	2431	2456	2505	2422
		2381	2381	2427	2533	2427	2423	2381	2437	2547	2427
108	2384	2422	2422	2533	2579	2516	2592	2534	2607	2641	2656
		2515	2425	2533	2650	2516	2559	2559	2627	2637	2650
109	2592	2632	2632	2715	2848	2687	2778	2774	2892	2884	2753
		2632	2632	2715	2835	2687	2773	2793	2873	2836	2872
110	2671	2817	2864	2956	2957	2778	2817	2865	2956	2957	2777
		2844	2724	2938	2914	2756	2947	2900	2927	2954	2933

Table 21: Network profits applying SRRA and BRRA for self-created instances obtaining 45 requests in total. Brighter row: SRRA. Darker row: BRRA.

I27	P_{sr} P_{br}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
SRRA	9,3	4,2	11,8	16,4	11,2	16,2	19,1	17,6	17,9	19,3
BRRA	6,0	4,5	13,4	15,8	10,7	15,6	18,7	16,4	17,3	16,8
I45										
SRRA	3,7	2,9	6,2	9,9	4,6	8,4	6,4	9,8	11,0	8,0
BRRA	3,8	2,6	5,6	10,5	4,2	8,6	8,0	9,5	11,0	8,4

Table 22: Collaboration gain $\boldsymbol{\theta}$ in percent for self-created instance set I27 and I45.

The outcome of the CCRP handling numerous customers shows very interesting results. There is strong evidence that the solution quality in terms of the collaboration gain decreases with an increasing number of customers. Whereas the collaboration gain for the heuristically solved transportation problem for Set I yields 63% for SRRA and 64% for BRRA applying the standardized reassignment method P_{sr} or P_{br} , the collaboration gain diminishes continuously from I27 to I45. For I27 the average collaboration gain achieves 9,3% for SRRA and 5,9% for BRRA and for I45 it is further downsized to 3,7% and 3,8%. In contrast, it can be assumed that the loss due to decentralization φ increases because there is probably high potential that a central planning approach achieves heightened network profits.

Furthermore, it can be assumed that for the underlying model an exact algorithm for solving the transportation problem also sustains a decreasing collaboration gain when servicing numerous customers. As mentioned already in Section 4.5.4, this is due to the inefficient scheme of evaluating the requests. Therefore, the count of request reassignments for an instance set serves as an indicator. For the initial instance Set I, the setup of Berger and Bierwirth and the alternative implementation faced approximately five iterations for SRRA and four for BRRA. The number of reassignments only shifts marginally for problem sets with augmented customers as illustrated in Table 23, where for I27 applying SRRA (and respectively BRRA) an average of about 8 (3) and for I45 a mean of 7 (4) reassignments occur.

Algorithm	P_{sr} / P_{br}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1	Mean
Average runtime in seconds											
I27											
SRRA	18	11	18	26	17	37	72	36	33	50	32
BRRA	22	24	43	38	34	249	337	143	162	303	135
I45											
SRRA	73	72	111	157	76	226	193	233	216	190	155
BRRA	99	99	142	255	160	1210	1136	967	832	945	585
Average number of request reassignments											
I27											
SRRA	8	4	9	10	6	16	19	14	12	16	11
BRRA	4	3	5	6	4	13	16	11	11	14	9
I45											
SRRA	7	6	10	14	7	19	16	21	20	18	13,8
BRRA	5	3	6	8	6	19	18	18	15	19	11,5

Table 23: Average runtime in seconds and average count of executed reassignments for instance set I27 and I45.

Another remarkable outcome is denoted by comparing the collaboration gains of SRRA and BRRA. Throughout all instance sets by Berger and Bierwirth BRRA outperforms SRRA. Though in the self-created instance set I27 SRRA yields a collaboration gain of 9,3% over a 6,0% gain of BRRA. In I45 BRRA performs just slightly superior with 3,8% compared to SRRA with 3,7%. This phenomenon is can be attributed to the fact that the SRRA accidentally enters a more preferable solution space than BRRA. Consequentially, it can be stated that with an increasing number of customers the discrepancy between SRRA and BRRA shrinks in case of solving the routing problem heuristically.

The outcome for the extensions is similar to the results of the original instances by Berger and Bierwirth. Using the collaboration gain θ as the performance indicator, the best solutions are obtained for various combinations in regard to the two problem sets I27 and I45 applying either SRRA or BRRA. The collaboration gain is increased by the extensions by up to 200% in comparison to the original reassignment setting P_{sr} and P_{br}. The condition of the auction system that carriers cannibalize the tours of each other still holds for processing the alternative implementation with numerous customers. This phenomenon can be surveyed in a recurring manner, especially in the problem set I27 which is illustrated in instance #91 in Table 24. In I45 this behavior is recognized in a mitigated attitude.

Number of requests carriers service finally				
Solution method	Carrier 1	Carrier 2	Carrier 3	Profit
$\boldsymbol{P_{nc}}$	9	9	9	1026
$\boldsymbol{P_{sr}}$	5	7	15	1241
TR	9	9	9	1049
$\boldsymbol{\alpha_2}$=1	8	9	10	1157
$\boldsymbol{\alpha_2}$=0	13	13	1	1210
TR & $\boldsymbol{\alpha_2}$=1	15	11	1	1276
CAR	5	6	16	1283
CAR & TR	1	11	15	1180
CAR & $\boldsymbol{\alpha_2}$=1	9	9	9	1203
CAR & $\boldsymbol{\alpha_2}$=0	12	14	1	1219
CAR & TR & $\boldsymbol{\alpha_2}$=1	16	10	1	1296

Table 24: The network profits and number of requests each carrier possesses after the auction procedure is completed. Example drawn from instance #91 (Set I27, SRRA).

Regarding the number of iterations during an auction run, there are slightly more reassignments observed for P_{sr} and P_{br} as in comparison to the original instances. The quantity of iterations rises if all requests are considered during an auction round or modified alpha values are applied. The runtime correlates in a positive manner to the number of reassignments, whereby the runtime of BRRA exceeds the runtime of SRRA considerably.[7] For I45 the program requires more than one minute computation time for each solution method of an instance.

[7] This is due to the implementation structure, which is explained in Section 5 in more detail.

5. Structure of implementation

In this section, the implementation is visualized on a high-level perspective in order to provide the basic structure of the program and highlight crucial activities like the auction process. Additionally, the main data structures are introduced to further clarify the implementation. The program is coded in the programming language C++ in the compiler tool Microsoft Visual C++ 2010 Express. The implementation follows the concept of Object-Oriented Programming (OOP) which is based on the programming methodology of objects rather than exclusively on functions and procedures. Objects are incorporated into superior classes where individual objects of a class can be grouped together. Objects of the same class share the same structures, but with each object different kinds of characteristics are associated. For example, in the current implementation of the collaborating carrier routing problem the *Carrier* class is used to simplify the problem to give each *carriers* object certain capabilities. The (three) carriers share similarities like they operate in the same business area, each of them possesses one vehicle with the same amount of capacity and they deliver pickup and delivery requests. But the carriers exhibit discrepancies according to the depot location or the possessed request portfolios. The majority of modern programming languages like Java, PHP, C/C++ utilize the principles of OOP because it facilitates the implementation in terms of structural and organizational issues.

5.1. General structure of framework

The framework of the program is presented in Figure 10 which is revealed by the flow diagram indicating the process of the program sequence in general.

Before the program is executed, the required settings are initialized by the user. Hereby the user controlled parameters determine the following execution modalities:

- Parameter for Double Insertion heuristic $\delta = 1{,}25$ or $\delta = 1{,}00$
- Auction type (SRRA or BRRA)
- If an auction iteration considers all requests (CAR)
- If reassignment of already auctioned request is allowed (TR)
- Revenue settings ($\alpha_2 = 2$, $\alpha_2 = 1$ or $\alpha_2 = 0$)

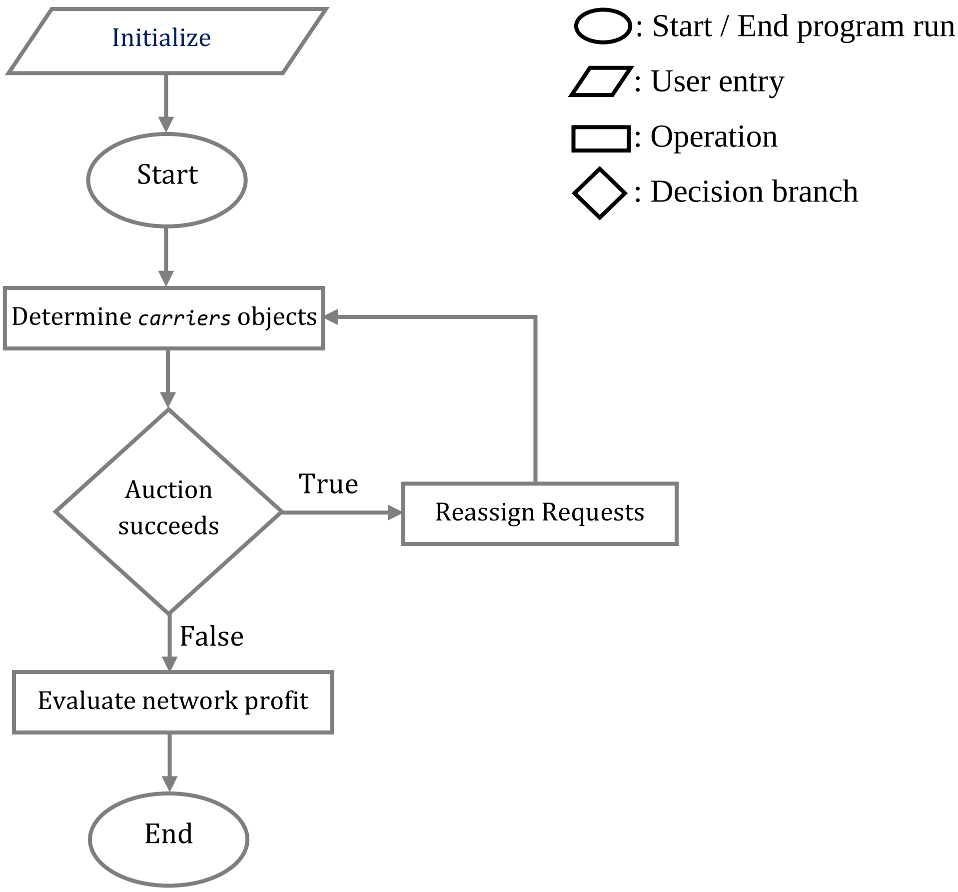

Figure 10: General flow diagram of the alternative implementation and corresponding legends

Every program run commences by reading in the data from an instance (see Table 3, p. 23). At this point some, very important data structures are generated in the program run and are presented below. The *Node* class represents the *node* object which contains properties like the x- and y-coordinates of the customers, precedence constraints and the direct distance between an order pair. A frequently used data container of the *carriers* object is a vector of type *node* which saves the depot and all requests owned by a certain carrier. An exemplification is given in Figure 11.

0	1	2	3	4
X=30 *Y=60*	*X=55* *Y=5* *(X*/Y*)=(26/52)* *Distance: 110,5*	*X=26* *Y=52*	*X=13* *Y=52* *(X*/Y*)=(53/52)* *Distance: 80*	*X=53* *Y=52*

Figure 11: representation of *vector<Node>all_nodes*. Figures above box: index position in vector. Inside box: data of *node* object.

This vector *all_nodes* depicts the data of two requests possessed by Carrier 2 (see p. 22). The design structure of this vector type remains always equal, that is on position 0 of *all_nodes* the data of the depot is saved, the odd number represents the pickup customer and the odd number plus one indicates the appendent delivery customer. The size of the vector is defined by one depot location plus the number of customer locations. Based on this representation style in the implementation, continuing the example illustrated in Figure 11, the vector containing the tour data is illustrated in Figure 12.

0	1	2	3	4	5
Depot	3	1	4	2	Depot

Figure 12: representation of *vector<int>tour*. Figure above box: index position in vector. Inside box: integers referencing to the index of vector *all_nodes*.

The vector *tour* of type integer displays the sequence of servicing the customer locations. The depot is located at first and last position, and the figures in the box are referencing to the index position of the related vector *all_nodes* to retrieve the data.

A major part of the program is to determine the *carriers* objects in order to receive the marginal profits of requests as discussed in Section 3.3. A *carriers* object holds data like the vectors presented above and all relevant data to calculate the marginal profit of possessed or potential requests. The following procedure for determining the marginal profits of a request is executed for the three carriers. In the implementation, this is performed by functions as shown below which process the incoming data and return the denoted output.

In a first step a distance matrix is initialized in form of a two-dimensional array according to the number of requests a carrier owns actually as shown in Figure 13.

```
// Initialization of the distance matrix for a carriers object
void Carrier::initializeDistanceMatrix()
{
// create a 2-dimensional array
// Size of matrix is determined by number of requests + depot
distance_matrix = new double*[all_nodes.size()];
for (unsigned int i = 0; i < all_nodes.size(); ++i)
        {
                distance_matrix[i] = new double[all_nodes.size()];
        }
}
```

Figure 13: Initialization of the distance matrix for a *carriers* object

As in the in the first run, each carrier possesses three requests, in the further program process the amount of requests may vary. Therefore, the size of the array is determined by the number of possessed requests plus the depot. In the ongoing program run the tour length is calculated by the Euclidean distance based on the distance matrix (see Section 3.3.2).

The following code illustration in Figure 14 represents the Double Insertion heuristic examined in Section 4.4.1.

```
// Evaluate Score values and determine position where order-pair is placed in the tour
// insertVertex() represents the double insertion heuristic
void Carrier::insertVertex()
{
// Iterate through vector holding all requests
for (unsigned int i = 1 ; i < all_nodes.size(); i++)
{
   // function checks if order-pair is already part of tour
   if (Non-visitedCustomer(i))
   {
      // Only consider the pickup customers of the all_nodes vector
      if (i%2)
      {
         // Variable holding the insert position
         int positionScore1 = 0;
         // Variable specifying value/score of a request in certain position in tour
         double score1Value = 0;
         // Score 1 is determined by the formula on p. xy
         calcSCORE1(&positionScore1,&score1Value,i);

         // Code block from line 20-23 resembles Score 1,
         int positionPickup = 0;
         int positionDelivery = 0;
         double scoreValue2 = DBL_MAX;
         calcSCORE2(&positionPickup, &positionDelivery, &scoreValue2, i);

         // Identify lower score and insert the order pair on conceived
         // location in tour vector
         if (score1Value < scoreValue2)
         {
            tour.insert(tour.begin()+positionScore1, i);
            tour.insert(tour.begin()+(positionScore1+1), i+1);
         }
         else
         {
            tour.insert (tour.begin()+positionPickup, i );
            tour.insert (tour.begin()+positionDelivery, i+1);
         }
      }
   }
}
}
```

Figure 14: Code fragment of the Double Insertion heuristic

It is notable that during the construction phase the precedence constraints are checked at no point because of the heuristic design developed by Renaud et al. (2000), it guarantees a feasible insertion procedure. In contrast to the tour improvement phase performed by the 3-opt algorithm, feasibility checks in regard to the precedence conditions are required. It is performed by checking for each pickup customer if the appendent delivery customer is located in a subsequent position on the tour which burdens the running time as examined in Section 4.1.2.

In the next step, the marginal revenue of a request is determined as shown in the code fragment below in Figure 15.

```
// Calculate the revenue of an order pair and save it to a vector
vector<double> Carrier::clcRevenueRequest()
{
        double revenue = DBL_MAX;
        // Empty the existing vector holding the revenues of requests
        revenueRequests.clear();
        // the vector pickup_nodes is designed like all_nodes, only saving pickup nodes
        for (unsigned int i = 0; i < pickup_nodes.size(); i++)
        {
                // Calculation of revenue (see p.
                // e.g. g->delta1 holds the constant 1,25
                revenue = g->delta1 + g->delta2*(pickup_nodes.at(i)->distance);
                revenueRequests.push_back(revenue);
        }
        return revenueRequests;
}
```

Figure 15: Code fragment of determining the marginal revenue of a request

Then the revenues are calculated (see p. 23) and saved to a vector. The values of revenues, marginal costs and marginal profits of requests are stored in the same way to provide a consistent structure for the ongoing calculations.

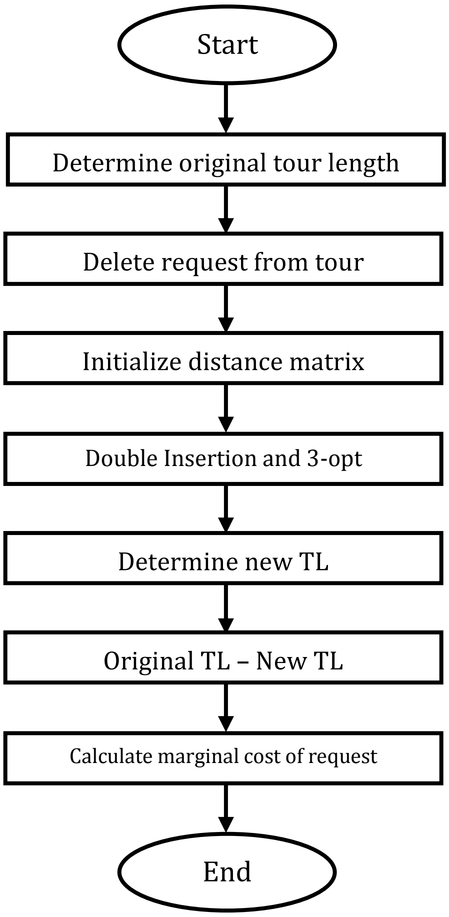

Figure 16 Flow diagram of determining marginal cost of a request

In the next step the marginal cost of a request is determined according to Section 3.3.3. The program execution is demonstrated in form of a flow diagram: At first, the original tour length of the actual route serviced by the carrier is determined. Next, the surveyed request is deleted from the tour. In the ongoing process, to derive the new tour with the excluded request, the distance matrix is updated and the routing is scheduled by the construction and improvement heuristics. Finally, the marginal tour length of the considered request is assessed and the marginal costs are deduced. After the marginal profits of requests are calculated, the determination of the `carriers` object is completed. Hence, all relevant data is available in order to execute the auction.

Coming back to the general program framework: The auction algorithms SRRA and BRRA are embedded in a Boolean function. According to the outcome of one auction round, the function returns `True` in case a reassignment of a request is carried out or `False` in case the reassignment procedure fails. In case of the function returning `True`, `carriers` objects are updated, and in the latter case of `False`, the determination of the network profits is initiated by utilizing the original revenue settings.

5.2. Implementation structure of SRRA

As a detailed explication of the SRRA is already provided in Section 3.4.2., in this section the sequence of operations executed by SRRA is presented in form of a flow diagram to illustrate the logic design of the implementation, as shown in Figure 17. Furthermore, the program flow in regard to the designed extensions of CAR and TR are pointed out.

In order to derive the candidate set, the program identifies for each carrier the request holding the lowest marginal profit. Here, the request which offers the lowest marginal profit is selected and the latter serves in the following as floor price. In case of applying the setting that an already auctioned request may not attend in further auction rounds, the program is required to clarify if the selected request already attended in a reassignment. If that request was reassigned earlier, another request is drawn out of the candidate set, otherwise the carrier holding this request is assigned as the auctioneer for this run. In case TR is active the auctioneer can be set immediately.

Therefore, the request is added to the current task-portfolio and its marginal request is determined, serving as the compensation price in the further bidding process. Subsequently, the program identifies how many bids (compensation prices) exceed the floor price. As an outcome, if no bid is above the floor price or the network profit is negative another request of the candidate set is considered. In case the reassignment succeeds, the Boolean SRRA function returns `true` and initiates an update for the `carriers` objects. Two scenarios are possible in order to refuse a reassignment: Firstly, in case the original settings are applied and not all requests are considered in an auction round, SRRA terminates if all requests in the candidate set are rejected. Secondly, CAR is active and all requests in the network were considered at least once. Then the function returns FALSE leading to an evaluation of the overall network profit.

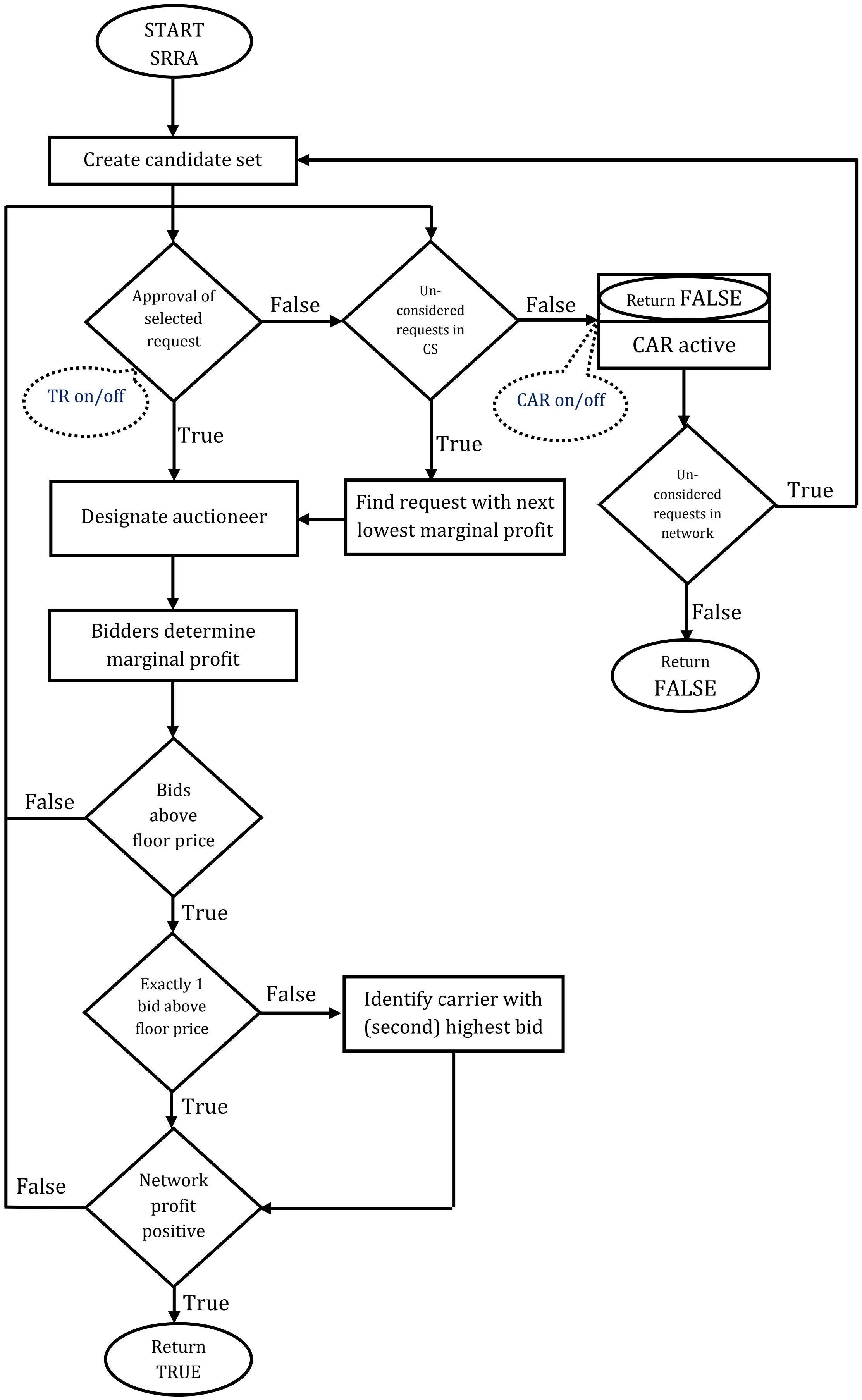

Figure 17: Flow diagram of the SRRA. CS: candidate set

5.3. Implementation structure of BRRA

The implementation part for executing BRRA is more complex than performing SRRA. In this section, a brief illustration of the program flow by BRRA is given in Figure 18 and the basic structure of solving the CAP is presented.

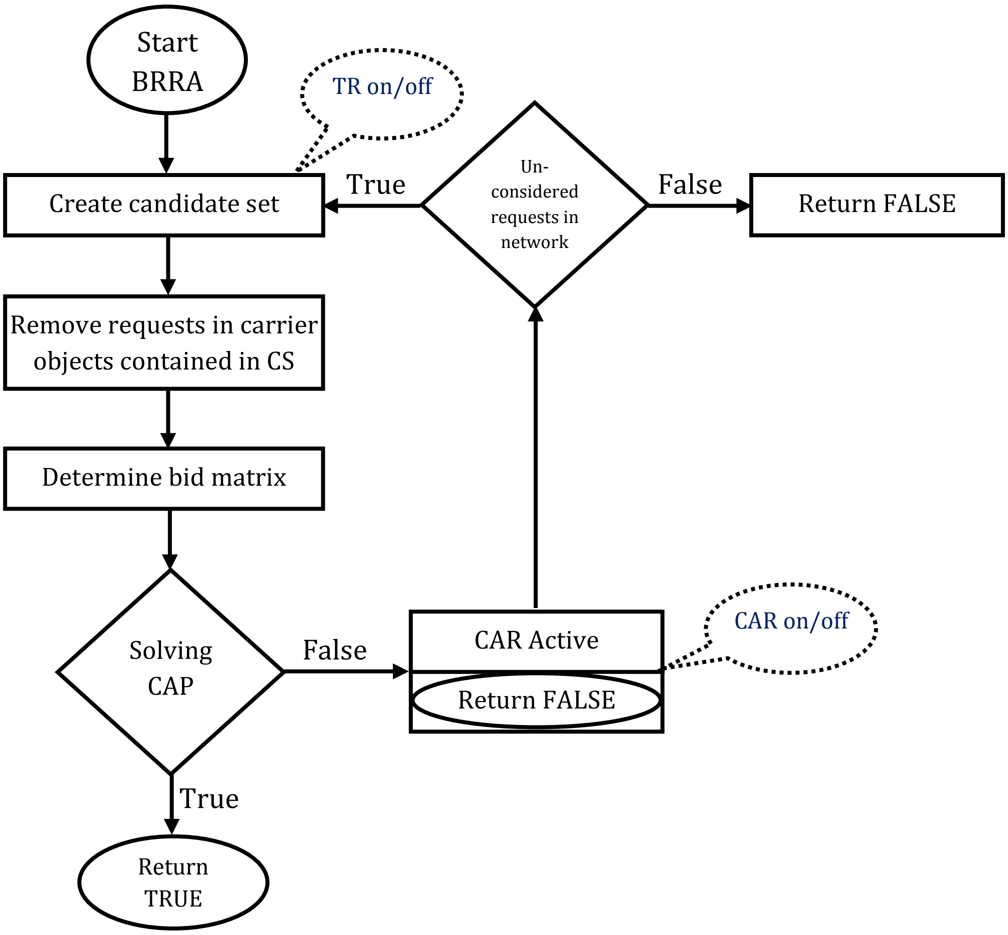

Figure 18: Flow diagram of BRRA

In a first step, requests indicating the lowest marginal profit for each carrier are placed into the candidate set under the consideration weather TR is active or not. From here on the implementation structure differs distinctly compared to SRRA because all possible subsets of the candidate set are composed as depicted in Section 3.4.3. In the following step, the initialization for determining the profit matrix occurs. Therefore, the requests which are composed in the candidate set are removed in the `carriers` object. Subsequently, each carrier incorporates the request(s) to its operational planning scheme to evaluate the marginal profit. The procedure is exemplified by a code fragment in Figure 19, when Carrier *0* evaluates the marginal profit containing the bundle of its own order-pair and request of Carrier 2.

```
// Superior hierarchy function determins the bid matrix
void Auction::initializeProfitMatrix()
{
   [...]
   // Carrier 0 assesses MP for the requests owned by itself and Carrier 2
   // carriers.at(2)->auctionPickup represents request of Carrier 2 inside CS
   bidMatrix[0][4] = add_Two_ProfitMargins(carriers.at(2)->auctionPickup, 0);
   [...]
}

// Called function derives Marginal Profit of request combination
double Auction::add_Two_ProfitMargins(Node* addPickup, int c)
{
   // Carrier 0 adds his own request
   carriers.at(c)->setRequestPair(addPickup);
   // Carrier 0 receives request of Carrier 2
   carriers.at(c)->setRequestPair(carriers.at(c)->auctionPickup);
   // Update carriers' data
   carriers.at(c)->determineNewTour();
   // In the subsequent section the marginal revenues and marginal costs of
   // the requests are assessed
   [...]
   // Actually calculating the marginal profit
   carriers.at(c)->clcSingleMargProfits();

   // restore earlier configuration: the added requests are removed again
   carriers.at(c)->resetNodeVecs();
   // return marginal profit to bid matrix
   return carriers.at(c)->SingleMargProfits;
}
```

Figure 19: Code fragment of Carrier 0 assesses bid value of request bundle consisting of own request and of request from Carrier 2

The marginal profit of this task combination is shown in the generalized bid matrix by the variable *e*, displayed in Table 25. In total 21 bid values are assessed an inserted into the bid matrix.

	0	**1**	**2**	**0 & 1**	**0 & 2**	**1 & 2**	**0 & 1 & 2**
Carrier 0	a	b	c	d	e	f	g
Carrier 1	h	i	j	k	l	m	n
Carrier 2	o	p	q	r	s	t	v

Table 25: Generalized bid matrix. Variables stand for the marginal profit of a request (combination) a carrier achieves.

The Combinatorial Auction Problem is implemented straightforward. Hence, all possible bid combinations are calculated and the combination which achieves the highest outcome is selected. In this case, three carriers are participating in the combinatorial auction and in total 27 bid combinations are evaluated as demonstrated in Table 26.

a+i+q	d+q	k+q	r+c	g
a+j+p	d+j	k+c	r+j	n
b+h+q	e+i	l+b	s+i	v
b+j+o	e+p	l+p	s+b	
c+h+p	f+h	m+a	t+a	
c+i+o	f+o	m+o	t+h	

Table 26: All possible bid combinations in CAP according to the bid variables provided in in the bid matrix illustrated in Table 25

In the implementation framework, solving the CAP is embedded into a Boolean function which returns *true* if a reassignment between *carriers* is executed or *false* in case no request exchange is performed. In other words, BRRA is terminated if the highest bid combination is yielded by *a,i & q* (see Table 25). Hence, the network profit achieves the best outcome in case each carrier services its own request offered to the candidate set.

6. Conclusion

This thesis deals with the subject of carrier collaboration networks. Freight forwarders establish a coalition on a horizontal level in order to allocate transportation requests among each other by a decentralized network structure. In Section 2.1, a broad examination of the potential gains of such a collaboration network has been presented. Addressees are rather small- and mid-sized carrier companies in anticipation of overcoming heightened competition and increased pricing pressures in the freight forwarding business area. According to the research, coalition members are able to lower their operating costs between 5% and 15% by exploiting the benefits of collaboration in terms of utilizing the fleets' capacity more efficiently and reducing deadheads. However, carrier collaborations are exposed to various challenges as discussed in Section 2.2. Major threats are depicted by data privacy issues as freight forwarders are willing to disclose internal business information only to a certain extent. Beside the carrier's autonomy, the challenges on collaborative routing are depicted for the single phases the network process undergoes: the evaluation and selection of transportation tasks which are offered to the request pool, the exchange mechanism for reassigning the requests and a fair profit allocation among the coalition members.

In the literature section (see 2.3), the three phases are analyzed individually according to recent research. Hereby, relevant methods and terms are presented which are applicable for carrier collaboration networks. Next, research contributions are presented which discuss the subject holistically. A conspicuous finding which could encourage further research is that the majority of research papers identifies data privacy in decentralized networks as a crucial criterion but does not incorporate the idea entirely as for example several studies embrace cooperating profit centers. Furthermore, there is no approach incorporating bargaining costs or transactions costs.

In Section 3, the Collaborative Carrier Routing Problem designed by Berger and Bierwirth is specified in detail. The authors provide a framework which proves the benefit of carrier collaboration on a quantitative basis by solving the underlying transportation problem to optimality. The carriers decide on the selection of which requests are outsourced to the central request pool independently. The reassignment of requests in the decentralized approach is performed by heuristic algorithms emulating a Vickrey Auction and a combinatorial auction. Their decentralized planning model achieves distinct cost savings over the non-collaborative approach while respecting the carrier’s desire of data and information privacy. However, the decentralized planning falls short considerably in regard to the central planning outcome.

The main contribution of this thesis is provided by a reproduced implementation of the model designed by Berger and Bierwirth. The basic modification consists in solving the TSPPD in form of a well-performing heuristic. The performance of processing the model heuristically delivers a very similar output for instance sets with low and medium competition: the aberration of the average network profit ranges from 1,0% to 6,1%. In case of a high competition area, the average network profit deviates from the output of Berger and Bierwirth between 10,2% (SRRA) and 17,8% (BRRA). Additionally, the original model of Berger and Bierwirth is expanded by basically three extensions, which are also combined with each other, in aspiration to increase the network profit of the collaboration. The extension CAR which considers all requests during the auction procedure increases the network profit clearly, but also exposes an additional information flow to the central authority. Berger and Bierwirth state that the only way to reduce the cost of decentralization "is to widen the amount of centrally known data" (Berger & Bierwirth, 2009, p. 638). In the alternative implementation, a modification is introduced which increases the network profit in various instances but does not require a further disclosure of data. Thereby the evaluation scheme is modified which determines the marginal profits of requests. As this assessment designates the requests which are outsourced to the central request pool, the original settings applied in the model of Berger and Bierwirth are altered in order to respect the marginal tour length of a request to a greater extent.

Another interesting finding is the high sensitivity of the model. For each instance, ten modes of solving SRRA and respectively BRRA are executed. For many instances the phenomenon is surveyed that the final portfolio of requests owned by the carriers differs distinctly for the various execution modes. Moreover, it seems that carriers "cannibalize" other coalition members' tours so that finally one carrier holds a bulk of requests. Hence, it can be assumed that carriers are able to manipulate the auction outcome by their bidding and offering behavior.

Furthermore, this thesis examines the outcome of the model for an increased number of customers. Berger and Bierwirth assume "that the more carriers compete within a customer area, the more benefit collaboration produces" (Berger & Bierwirth, 2009, p. 638). The designed experiments for the alternative implementation cover instances which are based on the style provided by Berger and Bierwirth. The initial problem operates with 18 customers and the self-created instances embrace 27 or rather 45 customer locations. In terms of solving the transportation problem heuristically, the assumption of Berger and Bierwirth cannot be verified as the collaboration gain decreases continuously with an increasing number of customers. At this point an examination is eligible in order to solve the central planning approach of the MDTSPPD exactly for instances with more customers. Besides, as already proposed by Berger and Bierwirth, further work may incorporate more advanced algorithms which are capable of anticipating the auction progress.

Bibliography

Ackermann, H., Ewe, H., Kopfer, H., & Küfer, K.-H. (2011). *Combinatorial Auctions in Freight Logistics.* Berlin, Heidelberg: Springer-Verlag.

Agarwal, R., & Ergun, Ö. (2010). Network Design and Allocation Mechanisms for Carrier Alliances in Liner Shipping. *Operations Research*(Vol. 58, No. 6), pp. 1726-1742.

Berbeglia, G., Cordeau, G., Gribkovskaia, I., & Laporte, G. (n.d.). Static pickup and delivery problems: a classification scheme and survey. *TOP*(15), pp. 1-31.

Berger, S., & Bierwirth, C. (2009). Solutions to the request reassignment problem in collaborative carrier networks. *Transportation Research Part E*(46), pp. 627-638.

Blazinskas, A., & Misevicius, A. (2010). *Combining 2-opt, 3-opt and 4-opt with k-swap-kick perturbations for the traveling salesman problem.* Kaunas: Kaunas University of Technology - Department of Multimedia Engineering.

Bloos, M., & Kopfer, H. (2011). *Vehicle routing and scheduling in carrier networks - Two heuristics for collaborative routing.* Proceedings of The 23nd Annual NOFOMA Conference.

Bolduc, M., Renaud, J., Boctor, F., & Laporte, G. (2008). A perturbation metaheuristic for the vehicle routing problem with private fleet and common carriers. *Journal of Operations Research Society*, S. 776-787.

Chu, C. (2005). A heuristic algorithm for the truckload and less-than-truckload problem. *European Journal of Operational Research*(165), S. 657-667.

Cruijssen , F., & Salomon, M. (2004). *Empirical Study: Order Sharing between Transportation Companies May Result in Cost Reductions Between 5 to 15 Percent.* Faculty of Economics . Netherlands: CentER Discussion Paper (No. 2004–80).

Cruijssen, F., Dullaert, W., & Fleuren, H. (2007). Horizontal Cooperation in Transport and Logistics: A Literature Review. *Transportation Journal*, pp. 22-39.

Dahl, S., & Derigs, U. (2011). Cooperative planning in express carrier networks - An empirical study on the effectiveness of a real-time Decision Support System. *Decision Support Systems*(51), pp. 620-626.

Dai, B., & Chen, H. (2011). A multi-agent and auction-based framework and approach for carrier collaboration. *Logistic Research*(3), pp. 101-120.

de Vries, S., & Vohra, R. (kein Datum). Combinatorial auctions: a survey. *INFORMS Journal on Computing*(15), S. 284-309.

Falcon, R., Li, X., Nayak , A., & Stojmenovic, I. (2010). The one-commodity traveling salesman problem with selective pickup and delivery: an ant colony approach. *In: Proceedings of the 2010 IEEE Congress on Evolutionary Computation(CEC2010)*, (S. 4326–4333).

Feillet, D., Dejax, P., & Gendreau, M. (2005). Traveling Salesman with Profits. *Transportation Science*(Vol. 12, No.2), pp. 188-205.

Jozefowiez, N., Glover, F., & Laguna, M. (2008). Multi-obkective Meta-heuristic for the Traveling Salesman with Profits. *J Math Model Algor*(7), pp. 177-195.

Kopfer , H., & Krajewska, M. (2007). Approaches for modelling and solving the integrated transportation and forwarding problem. *In: Corsten; Missbauer: Produktions- und Logistikmanagement*, pp. 439-458.

Krajewska, M., & Kopfer, H. (2006). Collaborating freight forwarding companies - Request allocation and profit sharing. *OR Spectrum*(28).

Krajewska, M., & Kopfer, H. (2009). Transportation planning in freight forwarding companies: Tabu search algorithm for the integrated operational transportation planning problem. *European Journal of Operational Research*(197), pp. 741-751.

Krajewska, M., Kopfer, H., Laporte, G., Ropke , S., & Zaccor, G. (2008). Horizontal cooperation among freight carriers: request allocation and profit sharing. *Journal of the Operational Research Society*(59), pp. 1483-1491.

Kwasnica, A., Ledyard, J., Porter, D., & DeMartini, C. (2005). A new and improved design for multi-object iterative auctions. *Management*(51), pp. 419-434.

Lee, C.-G., Kwon, R., & Ma, Z. (2007). A carrier's optimal bid generation problem in combinatorial auctions for transportation procurement. *Transportation Research Part E*(43), pp. 173-191.

Meixell, M., & Norbis, M. (2008). A review of the transportation mode choice and carrier selection literature. *The International Journal of Logistics Management*(Vol. 19, No.2), pp. 183-211.

Renaud, J., Boctor, F., & Quenniche, J. (2000). A heuristic for the pickup and delivery traveling salesman problem. *Computers & Operations Research*(27).

Ruijgrok, C. (2003). *European Transport: Insights and Challenges.* Amsterdam: Handbook of Logistics and Supply Chain Management.

Schönberger, J. (2005). *Operational Freight Carrier Planning.* Berlin, Heidelberg, New York: Springer.

Schwind, M., Kopfer, H., & Vykoukal, J. (2009). A combinatorial intra-enterprise exchange for logistics services. *Information Systems and E-Business Management*(7), pp. 447-471.

Skjoett-Larsen, T. (2000). *European Logistics beyond 2000.* United Kingdom: International Journal of Physical Distribution and Logistics Management.

Solomon, M. (2005). *http://w.cba.neu.edu/~msolomon/r101.htm*. Retrieved 11 08, 2013

Stadtler, H. (2009). A framework for collaborative planning and state-of-the-art. *OR Spectrum*(31), pp. 5-30.

Ting, C.-K., & Liao, X.-L. (2013). The selective pickup and delivery problem: Formulation and a memetic algorithm. (141), pp. 199-211.

Triki, C., Oprea, S., Beraldi, P., & Crainic, T. (2013). The stochastic bid generation problem in combinatorial transportation auctions. *European Journal of Operational Research*(http://dx.doi.org/10.1016/j.ejor.2013.06.013).

Vansteenwegen, P., Souffriau, W., & Van Oudheusden, D. (2011). The orienteering problem: A survey. *European Journal of Operational Research*(209), pp. 1-10.

Wang, X., & Kopfer, H. (2011). *Increasing efficiency of freight carriers through collaborative transport planning: Chances and challenges.* University of Bremen. Bremen: Cuvillier Verlag.

(2010). *Zahlen, Daten, Fakten aus Spedition und Logistik.* Bonn: DSLV - Deutscher Logistik- und Speditionsverband e.V.

Zhang, L., Xu, N., Yu, C., & Lui, P. (2009). Profit Allocation in Collaborative Less-Than-Truckload Carrier Alliance. *Proceedings of the IEEE: International Conference on Automation and Logistics.* Shenyang.

List of tables

List of figures

List of abbreviations

BRRA:	Bundle Request Reassignment Algorithm
CAR:	In an auction iteration all requests are considered (see Section 4.5)
CCN:	Collaborative Carrier Network
CCRP:	Collaborative Carrier Routing Problem
CLN:	Cooperative Logistic Network
DC:	Delivery Customer
DSS:	Decision Support System
LTL-PD:	Less than Truckload, Pickup and Delivery requests
MDTSPPD:	Multi-Depot Traveling Salesman Problem with Pickup and Delivery requests
OOP:	Object-Oriented Programming
OP:	Orienteering Problem
PC:	Pickup Customer
PDPTW:	Pickup and delivery Problem with Time Windows
SPDP:	Selective Pickup and Delivery Problem
SRRA:	Single Request Reassignment Algorithm
TR:	Auction tolerates the reassignment of already auctioned requests (see Section 4.5)
TSPP:	Traveling Salesman with Profits
TSPPD:	Traveling Salesman Problem with Pickup and Delivery requests
VRP:	Vehicle Routing Problem
WDP:	Winner Determination Problem

Appendix A

A Computational results: Obtained network profits

Results are treated as equal if values do not exceed a two percent range. (See Section 4.3)

Instance	P_{nc} BB	P_{nc}	P_{sr} BB	P_{sr}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
21	118	118	119	120	120	118	118	118	120	120	120	120	120
25	182	181	182	181	181	181	**191**	181	**191**	**191**	**191**	**191**	**191**
26	176	178	176	178	178	178	178	178	**187**	**187**	**187**	**187**	**187**
27	155	154	157	158	158	**163**	154	**163**	158	158	**163**	**163**	**163**
30	169	168	169	168	168	168	**174**	168	**174**	**174**	**174**	**174**	**174**

Table 27: Set A - SRRA - Obtained Profit of instances impacted due to extensions

Instance	P_{nc} BB	P_{nc}	P_{br} BB	P_{br}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
6	141	140	190	145	153	140	145	140	145	145	141	145	141
9	119	118	142	142	142	118	142	118	142	142	118	142	118
21	118	118	119	120	120	118	118	118	120	120	120	120	120
24	119	117	121	121	121	118	121	118	121	121	118	121	118
25	182	181	182	181	181	181	**191**	181	**191**	**191**	**191**	**191**	**191**
26	176	178	176	178	178	178	178	178	**187**	**187**	**187**	**187**	**187**
27	155	154	157	158	158	**163**	154	**163**	158	158	**163**	**163**	**163**
30	169	168	169	168	168	168	**174**	168	**174**	**174**	**174**	**174**	**174**

Table 28: Set A - BRRA - Obtained Profit of instances impacted due to extensions

Instance	P_{nc} BB	P_{nc}	P_{sr} BB	P_{sr}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
31	273	269	273	269	269	269	269	269	269	269	269	269	269
32	121	118	187	158	158	162	172	162	158	158	178	183	178
33	107	105	164	159	159	164	122	164	**179**	**179**	164	122	164
34	138	138	247	195	195	240	248	240	198	240	240	248	240
35	167	167	226	229	213	229	206	214	229	229	229	206	229
36	198	197	198	197	197	197	197	197	197	197	197	197	197
37	176	173	176	173	173	**220**	**220**	**220**	**220**	**220**	**220**	**220**	**220**
38	213	212	213	213	213	**289**	**289**	**289**	**237**	**237**	**289**	**289**	**289**
39	66	63	137	115	115	135	135	135	135	135	135	135	135
40	139	136	184	183	183	183	**238**	**183**	**235**	**238**	**238**	**238**	**238**
41	209	203	211	207	207	207	203	207	**215**	**216**	**215**	**214**	**216**
42	253	256	282	285	285	285	278	285	285	285	285	301	285
43	201	197	222	218	218	218	218	218	218	218	218	218	218
44	215	214	257	257	257	**282**	**287**	**282**	**287**	**290**	**287**	**287**	**290**
45	160	160	212	197	197	197	197	197	197	197	197	197	197
46	186	188	241	242	242	242	242	242	242	242	242	242	242
47	161	161	228	226	226	**241**	**230**	**241**	**233**	**241**	**241**	**233**	**241**
48	162	161	173	171	171	**197**	**197**	**197**	171	171	**197**	**197**	**197**
49	123	122	155	148	148	**172**	**172**	**172**	151	**172**	**172**	**172**	**172**
50	241	240	241	240	240	**245**	**263**	245	**263**	**263**	**263**	**263**	**263**
51	160	160	255	211	207	244	246	244	211	215	244	247	244
52	219	219	280	221	221	221	221	221	221	221	221	221	221
53	87	87	114	112	112	112	112	112	112	112	112	112	112
54	165	167	237	237	237	215	215	214	237	237	215	215	**266**
55	158	157	210	207	181	207	**215**	181	210	**217**	**212**	**215**	**217**
56	155	153	229	193	196	193	217	196	198	205	198	217	205
57	303	302	349	331	348	**357**	**357**	**357**	**353**	348	**358**	**358**	**358**
58	232	233	303	255	246	268	278	268	278	265	268	278	268
59	344	342	344	342	342	342	342	342	**350**	**350**	**359**	**359**	**359**
60	288	288	378	318	318	341	342	341	380	380	342	342	360

Table 29: Set O - SRRA - Profit obtained by Berger and Bierwirth, initial solutions of the alternative implementation and the various extensions

Instance	P_{nc} BB	P_{nc}	P_{br} BB	P_{br}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
31	273	269	273	269	269	269	269	269	269	269	269	269	269
32	121	118	187	173	152	117	172	117	173	158	162	183	162
33	107	105	164	159	159	**177**	**173**	**177**	**179**	**179**	**177**	**177**	**177**
34	138	138	294	236	210	240	252	240	236	240	240	252	240
35	167	167	231	229	222	229	203	222	229	228	203	203	222
36	198	197	198	197	197	197	195	197	197	195	195	**210**	195
37	176	173	176	173	173	**220**	**220**	**220**	**220**	**220**	**220**	**220**	**220**
38	213	212	213	213	213	**289**	**289**	**289**	**250**	**237**	**289**	**289**	**289**
39	66	63	169	115	115	132	136	132	116	116	132	136	132
40	139	136	184	183	183	183	**238**	183	**235**	**235**	**238**	**239**	**238**
41	209	203	211	207	207	203	207	203	**214**	**214**	**216**	204	207
42	253	256	282	285	285	285	**307**	285	285	273	285	**307**	285
43	201	197	222	218	218	218	218	218	218	218	218	218	218
44	215	214	257	257	257	**308**	**273**	**308**	**300**	**290**	**308**	**268**	**308**
45	160	160	212	209	197	209	209	209	209	209	209	209	209
46	186	188	241	242	242	242	242	242	242	242	242	242	242
47	161	161	228	226	226	**241**	230	**241**	**241**	**241**	**241**	**233**	**241**
48	162	161	199	197	197	197	197	197	197	197	197	197	197
49	123	122	172	172	172	121	172	121	165	170	145	165	170
50	241	240	241	240	240	**245**	**263**	**245**	**263**	**263**	**263**	**263**	**263**
51	160	160	212	214	211	**250**	**246**	**250**	201	187	**250**	**247**	**250**
52	219	219	300	221	221	229	221	221	229	221	229	211	221
53	87	87	114	112	112	87	112	87	112	112	87	112	87
54	165	167	237	237	237	237	237	237	237	237	237	237	237
55	158	157	205	207	181	207	**231**	207	**212**	**247**	**212**	**232**	**208**
56	155	153	229	196	198	153	217	153	196	205	187	217	217
57	303	302	349	348	348	**357**	**357**	**357**	348	348	**357**	**357**	**357**
58	232	233	255	255	255	**278**	**278**	**278**	**278**	**278**	**278**	**278**	**278**
59	344	342	344	342	342	342	342	342	**359**	**359**	**359**	**359**	**359**
60	288	288	378	318	318	**409**	**409**	**409**	380	380	**409**	**409**	**409**

Table 30: Set O - BRRA - Profit obtained by Berger and Bierwirth, initial solutions of the alternative implementation and the various extensions

Instance	P_{nc} BB	P_{nc}	P_{sr} BB	P_{sr}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
61	139	140	268	214	214	214	216	214	216	216	216	216	216
62	102	100	272	230	187	250	231	236	**251**	**295**	250	250	**284**
63	142	142	265	177	177	177	220	117	177	177	177	231	177
64	91	91	158	143	143	**197**	**197**	**197**	**212**	**212**	**212**	**212**	**212**
65	176	176	189	188	188	**264**	**258**	**244**	**233**	**325**	**286**	**258**	**265**
66	141	141	307	308	299	**320**	**344**	**320**	308	308	**320**	**344**	**320**
67	283	283	283	283	283	**369**	**347**	**369**	**369**	**369**	**369**	**369**	**369**
68	234	236	288	289	289	**305**	**405**	**307**	**317**	**319**	**317**	**405**	**319**
69	170	170	259	237	202	237	230	237	**281**	244	237	237	237
70	202	203	314	304	265	287	287	274	305	293	287	287	287
71	158	159	332	295	295	305	295	**343**	**337**	**351**	**337**	301	**348**
72	84	83	128	**271**	**201**	**271**	**254**	**201**	**271**	**254**	**271**	**254**	**254**
73	171	173	228	232	232	**271**	**302**	**271**	**347**	**347**	**296**	**302**	**309**
74	303	302	303	**320**	**320**	**389**	**396**	**389**	**357**	**450**	**397**	**396**	**451**
75	163	161	366	346	346	346	346	329	346	**379**	346	346	**379**
76	343	342	458	441	439	441	441	439	441	456	441	441	456
77	210	209	338	284	284	316	337	316	337	**357**	**357**	**357**	**357**
78	224	224	289	253	253	**342**	**340**	**313**	**309**	**309**	**342**	**340**	**342**
79	164	151	307	243	243	256	**319**	256	243	243	**327**	**327**	304
80	239	240	414	357	357	412	421	356	357	357	412	421	**441**
81	61	62	61	**162**	**99**	**235**	**233**	**233**	**162**	**187**	**235**	**233**	**233**
82	52	52	185	181	92	**199**	165	123	181	**215**	**199**	**205**	**199**
83	253	251	559	388	388	409	409	409	445	456	409	409	444
84	203	203	358	327	330	330	330	334	327	358	330	330	334
85	237	238	492	379	379	385	363	385	379	385	385	363	385
86	281	282	465	395	395	414	396	414	414	414	414	396	414
87	185	162	406	225	225	225	253	225	253	253	253	253	253
88	312	311	331	**373**	**373**	**395**	**402**	**396**	**379**	**379**	**395**	**402**	**402**
89	340	337	459	369	369	369	378	369	369	369	369	378	369
90	256	256	527	363	367	393	347	393	363	367	393	346	393

Table 31: Set I - SRRA - Profit obtained by Berger and Bierwirth, initial solutions of the alternative implementation and the various extensions

Instance	P_{nc} BB	P_{nc}	P_{br} BB	P_{br}	TR	α_2=1	α_2=0	TR & α_2=1	CAR	CAR & TR	CAR & α_2=1	CAR & α_2=0	CAR & TR & α_2=1
61	139	140	320	230	231	223	217	230	230	231	243	216	230
62	102	100	187	168	187	**302**	**249**	**236**	168	**295**	**302**	**249**	**247**
63	142	142	265	177	177	177	244	177	184	204	184	233	204
64	91	91	158	143	143	**183**	**197**	**183**	**212**	**212**	**185**	**212**	**212**
65	176	176	189	188	188	**265**	**271**	**261**	**312**	**312**	**317**	**272**	**317**
66	141	141	378	320	251	320	300	320	320	320	320	300	320
67	283	283	283	283	283	**369**	**347**	**369**	**369**	**369**	**369**	**347**	**369**
68	234	236	417	405	405	405	405	405	405	405	405	405	405
69	170	170	258	215	215	**274**	244	**295**	247	**261**	**274**	244	**295**
70	202	203	237	**259**	239	**266**	**276**	**287**	**276**	**265**	**266**	**269**	**287**
71	158	159	382	343	343	280	343	276	343	348	285	343	343
72	84	83	168	**272**	**167**	**272**	**254**	**254**	**272**	**272**	**272**	**254**	**254**
73	171	173	228	**236**	**232**	**292**	**309**	**347**	**270**	**297**	**292**	**309**	**347**
74	303	302	327	**450**	**327**	**450**	**428**	**450**	**450**	**412**	**450**	**428**	**450**
75	163	161	464	346	346	346	346	329	346	346	346	346	346
76	343	342	573	468	439	468	468	439	468	456	468	468	456
77	210	209	338	284	284	316	337	316	337	**342**	**357**	337	**357**
78	224	224	363	290	290	342	342	342	342	324	342	342	342
79	164	151	408	243	243	355	355	355	**243**	243	355	355	355
80	239	240	418	384	320	372	382	364	384	**424**	372	404	**427**
81	61	62	302	192	162	192	200	192	192	162	192	200	202
82	52	52	293	91	91	162	206	127	128	128	162	206	198
83	253	251	582	449	456	449	510	449	449	456	449	510	449
84	203	203	403	327	330	305	305	305	327	382	309	309	309
85	237	238	492	350	350	350	365	350	350	350	350	365	350
86	281	282	465	395	395	415	415	398	414	414	415	415	415
87	185	162	406	225	225	225	253	225	253	313	253	253	253
88	312	311	482	373	373	402	409	396	379	379	402	409	402
89	340	337	459	369	369	369	378	369	369	369	369	378	378
90	256	256	527	377	384	420	393	381	377	384	420	393	381

Table 32: Set I - BRRA - Profit obtained by Berger and Bierwirth, initial solutions of the alternative implementation and the various extensions

Appendix B

B Abstracts

B.I. English

This master's thesis deals with the topic of collaborative routing where transportation requests can be reassigned among carriers. The goal is to maximize the total network profit while all individuals are better off. Hereby, cost savings are achieved by exploiting economies of scope in terms of minimizing empty travel miles and cost savings are gained by economies of scale by integrating several requests into one tour. The thesis addresses the potential gains of collaborative routing as well as the major challenges. The first part of the literature review will give an overview of actual research papers which are contributed to the topic of carrier collaboration networks and examine partial phases in detail. In the second part, the review focuses on research papers which discuss collaborative routing networks holistically. The methodology encompasses a description of the applied methods and the problem-configuration is denoted.

The emphasis of this thesis is based on the work of Berger and Bierwirth published in 2010: *Solutions to the request reassignment problem in collaborative carrier networks*. The authors design and solve the Collaborative Carrier Routing Problem (CCRP) by reassigning transportation requests and thus maximizing the total profit of the collaborative carrier network. The transportation requests are reassigned by two kinds of algorithms which represent either a Vickrey Auction or a combinatorial auction.

The integrated tour planning method constitutes a Traveling Salesman Problem with precedence constraints (TSPPD) and is solved by exact algorithms.

In this thesis an alternative implementation for the CCRP is designed with the main difference of solving the routing problem heuristically. The motivation of this alternative implementation is to analyze the impact of solving the transportation problem of the CCRP heuristically and compare the results to the outcome derived by Berger and Bierwirth. Beside an in-depth analysis of the alternative implementation of the CCRP, the model of Berger and Bierwirth is extended in three different ways in anticipation of increasing the overall network profit. Additionally, the CCRP is examined for instances with more than 18 customer locations as conducted by Berger and Bierwirth. Overall, the analysis of the alternative implementation obtains not yet reported findings in regard to

the work of Berger and Bierwirth, like the disadvantageous procedure of evaluating the marginal profits of requests and the high sensitivity of the model due to changes in the settings. Moreover, the results of Berger and Bierwirth are outperformed by the implemented extensions in numerous instances though heuristics are applied in the tour planning process.

B.II. Deutsch

Diese Masterthesis beschäftigt sich mit dem Thema der kollaborativen Routenplanung, welche es ermöglicht Transportaufträge von Frachtführern neu zuzuordnen. Das Ziel ist den ganzen Profit des Netzwerkes zu maximieren unter der Voraussetzung, dass alle teilnehmenden Transporteure von der Zusammenarbeit profitieren. Kostenvorteile werden aufgrund zweierlei Gründe erzeugt, zum einen aus der Nutzung von Verbundeffekten, welche die Anzahl von Leerfahrten minimiert und zum anderen durch Skalenerträge, dass es erlaubt mehrere Aufträge in einer Tour zu bündeln. Im Literaturteil der Thesis wird das Potenzial der kollaborativen Routenplanung vorgestellt sowie die diversen Problemstellungen und Herausforderungen dem diese gegenüberstehen. Der erste Teil der Literaturauswertung befasst sich mit aktuellen Forschungsarbeiten, welche sich mit dem Themenbereich von Kooperationsnetzwerken in der Tourenplanung befassen, dabei aber nur einzelne Phasen berücksichtigen. Im zweiten Teil der Auswertung werden die Arbeiten vorgestellt, welche die kollaborative Tourenplanung als Ganzes diskutieren.

Der Hauptteil der Thesis basiert auf der Forschungsarbeit von Susanne Berger und Christian Bierwirth, welche im Jahr 2010 unter dem Titel „Solutions to the request reassignment problem in collaborative carrier networks" veröfftentlicht wurde. Die Autoren entwickeln und lösen das Collaborative Carrier Routing Problem (CCRP). Der Gewinn des Kooperationsnetzwerkes wird maximiert unter Anwendung zweierlei Heuristiken zur Auftragsverteilung, welche in der Praxis vergleichbar mit einer Vickrey Auktion und eine kombinatorischen Auktion sind. Die integrierte Methode zur Lösung des Transportproblems beruht auf dem Problem des Handlungsreisenden mit Vorrangbeziehungen (TSPPD), welches die Autoren mithilfe eines exakten Verfahrens lösen. Im Zuge dieser Thesis wurde eine alternative Implementierung entwickelt, welche das im CCRP zugrunde liegende Transportproblem heuristisch löst. Die Forschungsfrage beinhaltet unter anderem, welche Auswirkungen der heuristische Lösungsansatz auf das Model hat. Zudem wird die alternative Implementierung auf drei verschiedene Arten erweitert, welche untereinander kombinierbar sind, um den Profit des Netzwerks zu erhöhen. Außerdem erlaubt die heuristische Herangehensweise bei der Lösung des Tourenproblems eine Analyse des Models bei einer gesteigerten Problemgröße mit mehr Kunden.

Schlussendlich kann die detaillierte Analyse der alternativen Implementierung noch nicht aufgeführte Erkenntnisse über das Model von Berger und Bierwirth liefern. Dies betrifft zum einen die unvorteilhafte Evaluierung der Grenzerträge von Aufträgen und zum anderen die hohe Sensibilität des Netzwerkprofits bei unterschiedlichen Ausführungen des Models. Außerdem kann durch die konzipierten Erweiterungen der alternativen Implementierung der Profit des Netzwerks in einigen Instanzen erhöht werden, unter Berücksichtigung, dass das Tourenplanungsproblem heuristisch gelöst wird.

Appendix C

C Curriculum Vitae

Daniel Kaml

Ausbildung

Universität Wien	
Masterstudium Internationale Betriebswirtschaftslehre	**2011-2014**
Bakkalaureatsstudium Betriebswirtschaftsalehre	**2006-2011**
Universität Duisburg Essen	
Associate Business Foundation & Integration with SAP ERP 6.0 EHP5 – *SAP Certified*	**2012-2013**
Institut für Sport und Touristik (IST)	
Fernstudium Fußballmanagement – *Zertifizierter Fußballmanager* (*IST)*	**2010-2011**
Gisela Gymnasium München	
Abitur	**2005**

Vollzeitarbeitserfahrung während des Studiums

Robert Bosch Car Multimedia GmbH, Penang, Malaysia	
Traineeship Kunden-, Material- und Produktionsplanung	**2011**