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**Article**

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# Bundle selection approaches for collaborative practical-oriented Pickup and Delivery Problems

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## ABSTRACT

Due to the increasing price pressure in the less-than-truckload (LTL) market, horizontal cooperation is an effective and efficient way for small- and medium-sized LTL carriers to enhance their profits by exchanging requests. For this purpose, a decentralized auction-based collaboration framework has proven to provide a good approach. In this paper, such a collaboration framework is adopted and extended by applying it to a practical-oriented routing problem, the Pickup and Delivery Problem with Time Windows and Heterogeneous Vehicle Fleets. Particularly, we analyse the bundle selection process made by the auctioneers, which is a stochastic problem and specify which requests are supposed to be offered together in a bundle to the cooperating carriers. For the purpose of solving the selection problem properly, we implement a new procedure required due to the characteristics of the considered routing problem: a scenario-based bundle selection approach. In order to make this approach applicable, two pre-selection techniques (cluster- and neural network-based) are developed. Our approach is evaluated on 240 collaboration network instances created from well-known pickup and delivery research data sets generated by Li and Lim (2001). The collaboration framework results are compared with respect to the profit to individual transportation planning of each carrier (lower threshold) as well as centralized transportation planning of all carriers (upper threshold). It can be shown that the auction-based collaboration approach is up to 43.49% better than the individual planning as well as exhausts at least 53.5% of the centralized transportation planning potential on average.

## 1. Introduction

The German less-than-truckload (LTL) market is strongly dominated by small- and medium-sized freight carriers. About 60% of them have small vehicle fleets consisting of at most 10 vehicles with different capacities (cf. Schiller et al., 2017). In the LTL sector, several transportation requests are consolidated into one truck as a rule. The freight of each request is typically transported from an origin (pickup customer) to a destination (delivery customer). Consequently, different point-to-point transportation requests must be served. The resulting Pickup and Delivery Problem (PDP) for a carrier consists of designing a set of routes with maximum profit (or minimum costs) for a vehicle fleet positioned at the depot. The routes must meet pairing and precedence constraints of pickup and delivery customers. In addition, we assume that time windows (TW) at the customer locations and heterogeneous vehicle (HV) capacities must be observed. Thus, we consider a Pickup and Delivery Problem with Time Windows and Heterogeneous Vehicle fleets (PDPTWHV) as underlying routing problem.

Due to the increasing price pressure in the LTL market, small- and medium-sized carriers have to develop solutions to maintain their competitive ability. A possible and clever strategy to stay in business is to affiliate in horizontal cooperations for *collaborative* transportation planning. In 2015, 20% of the top 25 players in the LTL market (taking revenues into account) were already organized in cooperations (cf. Statista, 2017). In such cooperations, the participating carriers exchange transportation requests. Thereby, carriers often offer the requests that seem to be unattractive for themselves in an *auction* process. The requests are stored in an auction pool, which is managed by a central entity (the *auctioneer*). From this pool, the auctioneer *selects bundles* of requests that carriers can bid on (Bundle Selection Problem, BuSP). Each carrier calculates the bid value for a bundle which specifies the quality of the bundle for the corresponding carrier. After the bidding process, the auctioneer re-assigns the bundles of requests to the participating carriers through solving the Winner Determination Problem (WDP). At the end, the overall profit improved by the auction

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is distributed as fairly as possible to all partners. Ideally, no carrier should be worse off after exchanging requests.

The *bundle selection procedure* is the “heart” of the auction process, as selecting suitable bundles has the greatest impact on the efficiency of the auction process as well as the outcome of the cooperation. If too many (maybe even all possible) bundles are offered, the computational effort for calculating all required bids is too high due to the resulting combinatorial complexity, since each bid is generated through solving the underlying routing problem. If the bundles offered are unattractive or the number is too small, the surplus of the process for the individual carriers remains hidden. In contrast to Berger and Bierwirth (2010) as well as Gansterer and Hartl (2016b, 2018a), the proposed bundle selection approaches in this contribution do not operate on a fixed number of released requests per carrier. Our new strategy allows each carrier to offer all unattractive requests. This has the effect that there is a higher degree of freedom when determining attractive bundles. However, this releasing strategy often leads to many possible bundles (at least one million bundles in our instances), which have to be reduced thoughtfully. In order to solve the stochastic bundle selection problem efficiently in our collaboration framework, we present a *scenario-based selection* approach that estimates the bids for request bundles with respect to an attractiveness measure. Due to the huge number of possible bundles, the attractiveness measure cannot be evaluated on all bundles, and thus, pre-selection procedures have to be developed. To create reasonable bundles for the scenario-based approach, two different pre-selection techniques are implemented and compared with each other: a *cluster-based* and a *neural network-based* pre-selection approach. Thus, in the approach, stochastic optimization and machine learning techniques are combined in a reasonable way.

The paper is structured as follows: In Section 2, different collaborative transportation planning contributions as well as the auction-based solution framework applied in this paper are specified. In contrast to other papers using an auction-based request exchange approach, we provide a *first-price sealed bid double* auction. Moreover, it may happen that a carrier offers a relatively large number of requests, but then in turn receives relatively few requests. Due to this natural imbalance, we develop a new bundle-based profit allocation method to fairly allocate the profit gain received through the auction process. In Section 3, the PDPTWHV as well as the applied solution approach (a genetic algorithm; cf. Rüther and Rieck (2020) for the corresponding multi-depot problem) are briefly described. The decentralized collaboration framework is presented in detail in Section 4, while the scenario-based bundle selection approach with its cluster- and neural network-based pre-selection is proposed in Section 5. In Section 6, the results of individually and centralized transportation planning as well as decentralized auction-based planning with its bundle selection variants are provided and compared regarding the profit of transportation planning. Finally, we close the paper with a short discussion in Section 7.

## 2. Collaboration framework and literature review

The collaborative transportation planning in the LTL market can basically be divided into three categories: (a) centralized, (b) decentralized without auctions and (c) decentralized with auctions (cf. Gansterer and Hartl, 2018b as well as Cleophas et al., 2019).

In category (a), a central entity optimizes the transportation plans over all partners of the cooperation, i. e., a multi-depot routing problem has to be solved. The process requires *complete information* about all customer data. Contributions in this category mainly deal with game-theoretic profit allocation. For example, Krajewska et al. (2008) address a method of profit sharing based on the shapley value. In Liu et al. (2010), a variant of profit sharing is presented that minimizes the difference between relative saving regarding both, the profit allocation value and their individual costs. The variant is compared to game-theoretic profit sharing alternatives, e. g., the shapley value and the

nucleolus. Verdonck et al. (2016) also implement the profit sharing methods presented by Liu et al. (2010). For the profit allocation in Wang et al. (2019), the authors develop a shapley-value-based mechanism that seems to be very fair with regard to its closeness to the centre of the core.

Categories (b) and (c) are characterized such that each participant optimizes his own transportation plan himself and decides which requests to exchange. In category (b), the re-assignment of the released requests is done without auction mechanisms. Dahl and Derigs (2011) introduce a decentralized non-auction-based collaboration method with compensation payments. The procedure is used in a high dynamic PDPTW environment for an express carrier network and the solution obtained is very close to a centralized planning solution. Wang and Kopfer (2014) present an approach in which each carrier determines the requests to be released and their compensation price. Then, each carrier identifies the requests to be acquired and reveals the realization costs. A central entity solves the WDP and estimates if the subsequent request assignment has got less costs than the compensation prices. If this is the case, the re-assignment has been found. Otherwise, each carrier receives information about the winner determination and identifies again which requests to choose. As an extension, Wang et al. (2014) combine the framework described above with the possibility to outsource a request to subcontractors.

In this paper, we present a solution framework for decentralized auction-based transportation planning. Thus, category (c) is of central importance, where released requests are exchanged using auction mechanisms. However, before we consider the contributions in category (c) in Section 2.2, we elaborate on the applied collaboration framework in Section 2.1.

### 2.1. Solution framework for decentralized auction-based planning

Berger and Bierwirth (2010) are the first authors who have shown that the decentralized auction-based planning works very well for the Travelling Salesman Problem with Precedence Constraints (TSPPC) and has the advantage that only *little information* has to be exchanged between the participating carriers. Since this approach appears very promising and has been very popular in recent years (cf. Section 2.2), it will be applied in this paper for the collaborative PDPTWHV. In order to solve the pickup and delivery problem, a Grouping Genetic Algorithm (based on the one by Pankratz, 2005) is implemented (cf. Section 3). The genetic algorithm is used whenever a routing solution needs to be calculated (e. g., during the bidding process, cf. Section 4).

Our decentralized coordinated auction-based collaboration framework is based on a 5-phase procedure (cf. Fig. 1 excluding the routing steps) introduced by Berger and Bierwirth (2010). The phases can be described as follows:

- (i) Identification and release of unattractive requests by each carrier. Submission of requests to an auction pool.
- (ii) Selection of favourable request bundles by an auctioneer (solving the BuSP). Offering the bundles to the participating carriers.
- (iii) Determination of bids for each offered request bundle by each carrier.
- (iv) Solving the WDP (by implementing a Combinatorial Auction Problem, CAP) that carries out the optimal allocation of bundles to the carriers based on their bids.
- (v) Allocation of the profit achieved by the combinatorial auction.

The phases show that a complex auction process has to be implemented in which carriers act as sellers and buyers. In general, an auction mechanism should be designed by considering the following four properties: efficiency, budget balancing, individual rationality and (bayesian) incentive compatibility (cf. Krishna, 2010). Please note that satisfying all properties in one mechanism is not possible if there is

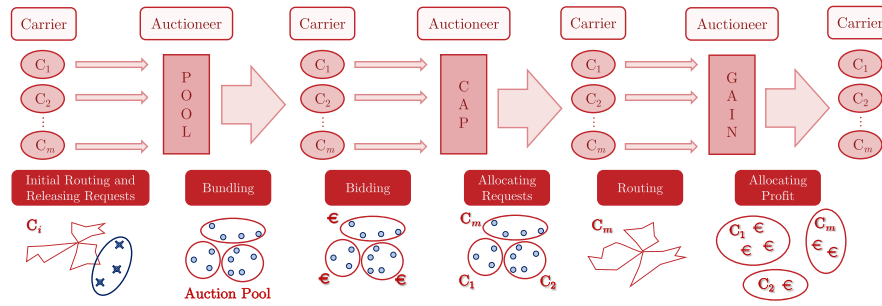


Fig. 1. Framework for collaborative PDPTWHV (cf. Berger and Bierwirth, 2010).

incomplete information (cf. Myerson and Satterthwaite, 1983). Incomplete information is given here, since the auctioneer does not know anything about the customer data of the requests that a carrier have not released (this data is the so-called *hidden information*). In order to achieve *efficiency*, the auctioneer usually allocates the requests such that the maximum possible outcome is gained from the auction (cf. Gansterer et al., 2019b). In a *budget-balanced* mechanism, the buyers' payment rule is defined such that all payments are completely allocated to all sellers. For designing an *individual rational* auction mechanism, each participating carrier should not be worse off after the auction is done. *Incentive compatibility* implies that each bidder's best strategy is to bid truthfully, because deviating from this strategy would result in a deterioration of the total as well as individual profit improvement. Since the Vickrey–Clarke–Groves (VCG) mechanism holds the last property (cf. Vickrey, 1961; Clarke, 1971; Groves, 1973), extensions of the VCG are used in many contributions (cf. Jain and Varaiya, 2007). However, truthful bidding as a dominant strategy can be achieved in a VCG mechanism only if the allocation is determined optimally (cf. Karaenke et al., 2019). Clearly, this cannot be guaranteed here, since the auctioneer does not offer all possibilities in the considered auction mechanism (cf. Section 5). Moreover, it can be shown that the VCG payment rule may lower the price for a bundle too much, so that the profit from the auction is less than the sum of minimum or ask prices previously set by the sellers in the double auction mechanism applied here. This will cause non-individual rationality or non-budget balance if some carriers are worse off after payment or if the auctioneer has to compensate for the loss, respectively. Since individual rationality and budget balance are important for the proposed framework, we implement in this contribution a *first-price sealed bid double auction*. In doing so, we will fall back to the initial solution if the profit improved by the auction is less than the sum of ask prices (double auction as described in McAfee and McMillan, 1987). Consequently, we achieve the auction properties needed for a successful request exchange (cf. step (iii) in Section 4).

## 2.2. Contributions in the field of decentralized auction-based planning

In the following literature review, we highlight papers from the field of decentralized auction-based planning (i.e., category (c)). However, the papers differ from our approach regarding the auction-based procedure or the underlying routing problem. In Dai and Chen (2011), each carrier is auctioneer and bidder at the same time in a multi-round auction, which is modelled as a multi-agent system. Each carrier determines the requests to be offered and the corresponding prices through a so-called outsourcing request selection problem. All other carriers then decide whether to accept these offers or not. If requests are chosen by many (few) carriers, the price will be reduced (increased) in the next round. The multi-round process is executed until a stopping criterion is met. Dai et al. (2014) extend the approach by a central entity acting as auctioneer, i.e., the carriers are only

bidders. In this procedure, the auctioneer sets outsourcing prices for requests and carriers decide which bundles they want to receive with respect to the prices. Afterwards, a combinatorial auction problem is solved by the auctioneer. If no solution can be found, e.g., due to non-disjunct request bundles, the auctioneer adjusts the prices for the next round and the carriers again determine which requests they want to buy. Consequently, carriers have to evaluate the same set of offered bundles multiple times. Moreover, it cannot be guaranteed that all requests are allocated (see, e.g., the cherry-picking problem described in Schopka, 2018). Contrarily to the possibility that the auctioneer forms bundles, Ackermann et al. (2011) consider the option that the bundle selection is performed by the carriers. The authors model a collaboration network based on combinatorial auctions in order to take the main goals relevant for the realization into account, e.g., data privacy protection or providing effective incentives for staying in the cooperation. Krajewska and Kopfer (2006) also focus on maintaining effective incentives for a combinatorial auction-based LTL carrier network. They apply a new profit sharing method based on game theoretical concepts and show in general that their method is individual rational, i.e., no carrier is worse off after the request exchange. Berger and Bierwirth (2010) introduce a decentralized collaboration framework with five consecutive steps (cf. Section 2.1). The individual phases of the framework and their effects on the solution quality are discussed, e.g., the use of single unit or combinatorial auctions for a TSPPC. Please note that the TSPPC is solved to optimality. Schopka and Kopfer (2017) analyse a Vehicle Routing Problem with Time Windows (VRPTW) and compare several pre-selection techniques for the determination of which request not to add to the auction pool. They show that there is no superior strategy in general, i.e., the best strategy always depends on the given data structure. Gansterer and Hartl (2016b) investigate the phases of Berger and Bierwirth (2010) and apply them to a TSPPC. Instead of the former exact approach used by Berger and Bierwirth (2010), they implement a heuristic for the routing in order to make the framework applicable for large collaboration networks. In addition, request evaluation strategies are introduced to find unattractive requests to be released to the auction pool. The authors indicate that strategies with regard to the distances between the depots and requests as well as with regard to the marginal profit are dominant for overlapping non-identical carrier regions and thus yield the best profit improvement. The question of how the complexity of the combinatorial auction included in the framework can be reduced, is studied in Gansterer and Hartl (2018a). Thereby, a stochastic mathematical model for the BuSP is formulated. Moreover to solve the BuSP, a genetic algorithm is implemented making use of a proxy in order to approximate the unknown objective function values. As a result, the number of bundles offered in the combinatorial auction can be reduced significantly. In Gansterer et al. (2019b), the profit sharing is examined comprehensively. The result of the profit sharing phase provides incentives for staying in the collaboration. Therefore, the authors present two incentive compatible approaches and show that both of them do not satisfy all theoretical



characteristics of a fair allocation mechanism. As information is a valuable good in collaboration, Gansterer et al. (2019a) investigate how aggregated information about the requests to be released can enhance the outcome of the collaboration. In Karels et al. (2020), the decentralized auction-based approach of Berger and Bierwirth (2010) is extended by several auction mechanisms which are compared on a collaboration network for carriers operating in the VRPTW field. They evaluate, e.g., the so-called *Limited Reassignment Auction* where the requests can be submitted as fixed bundles to the auction process or the so-called *Combinatorial Reassignment Auction* in which the participants are allowed to bid on self-created bundles additionally to the ones generated by the auctioneer.

To summarize, collaboration in the LTL market is promising and offers potential to improve the steps within the process, e.g., bundle selection, which is considered here. Additionally, the underlying vehicle routing problem to be solved for each carrier is different; it is based on a TSP, a VRP(TW) or a PDP. Especially, authors using the auction-based exchange mechanism also applied in this paper, study only rather simple routing problems (cf. Berger and Bierwirth, 2010; Gansterer and Hartl, 2016b, 2018a). Hence, we discuss a more practical-oriented routing problem (the PDPTWHV), which is solved by a Grouping Genetic Algorithm (GGA). Both the problem itself and the solution approach are described in Section 3. Additionally, the collaboration framework introduced in Section 2.1 has to be adjusted in some steps, which is described in detail in Sections 4 and 5.

### 3. Underlying routing problem and its solution approach

The practical-oriented PDPTWHV considered in this paper deals with requests in which goods have to be transported from pickup customers to corresponding delivery customers using the same vehicle. In the process, capacity constraints for the vehicles have to be observed. Since occupied loading ramps can lead to waiting times for vehicles and thus affect the transportation plan of carriers, customers are enabled to specify time windows in which the request has to be picked up or delivered, i.e., when the service should start. As the cooperation framework is developed especially for small and medium-sized carriers that have typically vehicles with different characteristics, we consider a heterogeneous vehicle fleet (three capacity types are used in the problem instances described in Section 6.1).

The routing problem (as an extension of a VRP) is  $\mathcal{NP}$ -hard and thus an effective and efficient heuristic solution approach must be developed. For the multi-depot PDPTWHV, Rüther and Rieck (2020) extended and implemented a Grouping Genetic Algorithm originally introduced by Pankratz (2005). The approach produces promising results and is therefore also used in our decentralized auction-based collaborative framework to solve PDPTWHV. For all terms and concepts related to genetic algorithms, see Eiben and Smith (2015). Please note that to evaluate the solution quality of the collaborative framework, centralized collaborative transportation planning (i.e., solving the multi-depot problem) can be used as an upper threshold for the profit (see Section 6).

In the GGA approach, a group-oriented genotype encoding is used, i.e., for each vehicle the served requests are stored in one gene. In Fig. 2, an example for a genotype encoding is displayed, where 9 requests have to be transported. In total, 3 vehicles (labelled with negative numbers) are available; request indices following after a vehicle index are served by the corresponding vehicle. Please note that the order in which pickup and delivery customers are visited is determined in the corresponding phenotype. An example route is described in Fig. 2 for vehicle 2, where  $p_r$  is the pickup and  $d_r$  the corresponding delivery customer of request  $r$ . It is important to mention that the GGA is able to handle infeasible solutions. Thus, if requests cannot be served due to certain constraints, they will be listed before the first vehicle index.

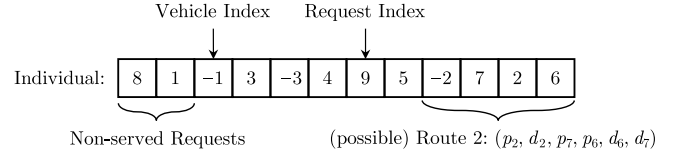


Fig. 2. Genotype encoding for the GGA with 9 requests and 3 vehicles.

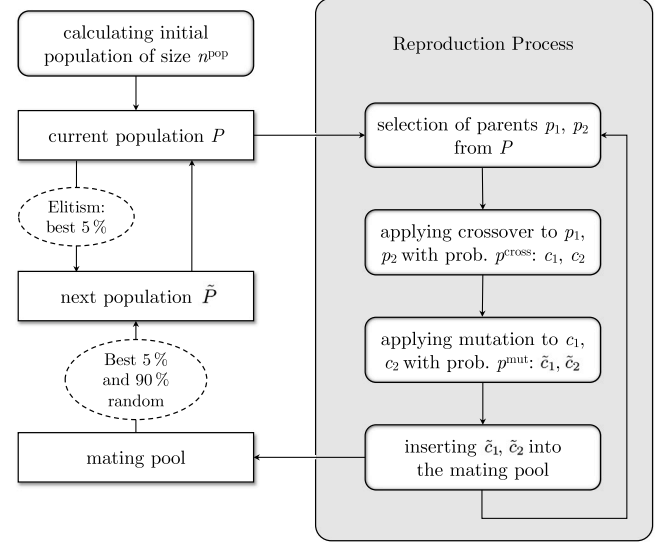


Fig. 3. Grouping Genetic Algorithm Framework with Mating Pool and Elitism.

In general, our GGA proceeds as follows (see Fig. 3). Initially, a population  $P$  of  $n^{\text{pop}}$  individuals is determined. We assume that each individual has a fitness value that is equal to the profit of the PDPTWHV solution minus a penalty term for all non-served requests. Consequently, this fitness value is to be maximized. In order to achieve a high level of diversity, we do not allow duplicates within the (initial) population. For this purpose, a comparison of fitness values, numbers of vehicles used and fixed costs is carried out, since each pair of the three attributes is not unique for comparing two individuals.

As long as the termination criterion has not been met (maximum number of generations created  $n^{\text{gen}}$ ), two parents  $p_1, p_2$  for generating offsprings are selected according to their fitness. With a probability of  $p^{\text{cross}}$ , a two-point crossover operator is applied to  $p_1$  and  $p_2$  in order to create two children  $c_1, c_2$ . Moreover, each child is modified by using one of the mutation operations with probability  $p^{\text{mut}}$ , and so, two mutated children  $\tilde{c}_1$  and  $\tilde{c}_2$  are generated. In case no operator is applied, the created offsprings are just clones of their ancestors. As population management technique, general replacement with elitism is performed using a mating pool. Hence, the generated offsprings  $\tilde{c}_1, \tilde{c}_2$  are first inserted into a mating pool, which has a size of  $1.5 n^{\text{pop}}$ . When the size of the mating pool is reached, the best 5% of the pool is transferred into the next generation. To make use of elitism, also the best 5% of the last generation is copied to the next generation. The remaining 90% is filled with randomly chosen individuals (without replacement) from the mating pool. Finally, the best individual regarding its fitness is selected as result after the GGA terminated. Please note that  $n^{\text{pop}}, n^{\text{gen}}, p^{\text{cross}}, p^{\text{mut}}$  are parameters that have to be set manually (see Table 4 in Appendix A).

### 4. Framework for the collaborative PDPTWHV

In order to apply the 5-phase procedure of Berger and Bierwirth (2010) introduced in Section 2.1 (cf. Fig. 1), we take the individual

steps and extend them for our purposes. In what follows, a detailed description of each step is given. For the notations of Sections 4 and 5, which are needed for the approaches implemented in the collaboration framework, we kindly refer to Table 3 in the Appendix (cf. Appendix A).

**Step (i): Identification of unattractive requests.** In order to identify unattractive transportation requests, evaluation techniques are used that depend on auction pool data and generally known carrier data, e.g., the ratio of revenue and request load, time-dependent characteristics or the depot locations of competitors. An extensive study shows that the request evaluation variants based on a cooperative strategy lead to the best results for the whole cooperation as well as for each individual carrier (cf. Gansterer and Hartl, 2016b). Hence, we assume that each carrier acts cooperatively. This is particularly true in our framework, since a non-cooperative strategy leads to the return of requests, e.g., such requests that are obviously badly located for the partners will be returned. Thus, a carrier  $c \in C$  releases requests  $r \in R$  holding condition (1):

$$\frac{\min_{\tilde{c} \in C \setminus \{c\}} \{\text{dist}(r, d_{\tilde{c}})\}}{\text{dist}(r, d_c)} \leq \frac{1}{1 - \varepsilon} \quad \forall c \in C. \quad (1)$$

The operator  $\text{dist}(\cdot, \cdot)$  characterizes the distance between request  $r$  and depot  $d_c$ ; more precisely, the sum of distances from  $d_c$  to the corresponding pickup and delivery locations is considered. Please note that operator  $\text{dist}(\cdot, \cdot)$  needs not only to include distances, as mentioned in the beginning of step (i), but it can also take other influences into account such as positions of time windows, request's revenue or the demand that has to be transported. The parameter  $\varepsilon \in [0, 1)$  controls how strictly the condition has to yield that the distance to the competing depot is smaller than to the own depot. If, e.g.,  $\varepsilon = 0.5$ , then due to (1) carrier  $c$  releases all requests that are at most twice as far away from a depot of a competing carrier as from the own depot. The number of requests holding condition (1) may vary from carrier to carrier. Contrary to Berger and Bierwirth (2010) as well as Gansterer and Hartl (2016b), we do not restrict the number of requests to be released in our approach in order to achieve a great potential for optimization. The larger the number of requests  $p$  included in the auction pool  $P$  is, the more exchange opportunities leading to a profit improvement are available. However, this results in a higher computational complexity; an auction pool of size  $p$  results in  $2^p - 1$  possible bundles of requests to be built (omitting the empty bundle). Therefore, placing a bid on each conceivable bundle is not practicable for the carriers (e.g., even for small auction pools with  $p = 10$ , each carrier has to submit over 1,000 bids). Consequently, the auctioneer must select bundles of requests “matching” to each other to ensure the generation of a sufficiently high profit from the auction.

**Step (ii): Bundle selection.** In the process of selecting bundles, the attractiveness of bundles must be addressed. This requires carefully chosen and comprehensive approaches, which are described in detail in Section 5.

**Step (iii): Determination of bids.** In our first-price sealed bid double auction (cf. Section 2.1), each carrier must determine an ask price (cf. Rahul and Varaiya, 2009) which a carrier wants to get for all offered requests and must calculate a bid for every bundle offered by the auctioneer. Let  $b_{m,B}$  be the bid and  $v_{m,B}$  the corresponding true valuation of bidder  $m$  for bundle  $B$ . Furthermore, let  $a_s$  be the ask price and  $v_s$  the corresponding true valuation of the seller  $s$ . Since the carriers are both, sellers and bidders, i.e., for simplicity we write  $m = s = c$ .

When bidding, auction participants may behave strategically, i.e., they maximize their own benefit through submitting bids deviating from their true valuation. An *incentive compatible* mechanism that yields truthful bidding is desirable, but particularly might result in violating one of the other properties in the considered double auction mechanism (cf. Gansterer et al., 2020). However, assuming that participants are aware of and weigh the following two cases, they are less likely to quote prices or bids that deviate from the true values.

1. Carrier  $c$  could lower his ask price ( $a_c < v_c$ ) or raise his bid ( $b_{c,B} > v_{c,B}$ ) for a certain bundle  $B$ . Since the ask price is the minimum price for the offered requests that is paid to the associated carrier within the auction process, the first strategy will lower the profit of  $c$ . Analogously, the second strategy will also reduce the carrier's profit if the carrier bids higher than the true valuation. In case the bundle is won for a bid of  $v_{c,B}$  anyway, this implies a profit loss of  $b_{c,B} - v_{c,B}$ .
2. Carrier  $c$  can set a higher ask price ( $a_c > v_c$ ) or lower his bid ( $b_{c,B} < v_{c,B}$ ). In both of the cases, the probability increases that there is not enough profit from the auction process to be allocated, i.e.,  $\sum_{c \in B} b_{c,B} \not\geq \sum_c a_c$  (see Eq. (5) in the WDP, step (iv)). This leads to the fall back solution, i.e., all requests are returned to their origin carriers, which also reduces the possible outcome of the auction.

Accordingly, it is possible to assume truthful bidding here. Then, the value of a bid can be assumed as the carrier's marginal profit with respect to the corresponding bundle. We thus calculate  $b_{c,B} = \text{profit}(\mathcal{R}'_c \cup B) - \text{profit}(\mathcal{R}'_c)$ , i.e., the difference of profits for carrier  $c$  coming from the solution with the retained requests  $\mathcal{R}'_c$  in combination with bundle  $B$  and the solution without bundle  $B$ . Please note that an ask price  $a_c$  is just referred to a carrier  $c \in C$ , since it describes the profit loss of  $c$  for submitting his requests  $\mathcal{R}_c \setminus \mathcal{R}'_c$  into the auction pool  $P$ , i.e.,  $a_c = \text{profit}(\mathcal{R}_c) - \text{profit}(\mathcal{R}'_c)$ . All profits are determined through solving the underlying routing problem using the Grouping GA described in Section 3.

**Step (iv): Winner determination problem.** In order to find the optimal bundle to carrier allocation, the WDP has to be solved. The detailed formulation of this problem depends on the auctioneer's objective and more basically on the auction at hand. Here, a multi-unit auction is considered, where the requests are to be allocated in bundles. The problem can be modelled as a combinatorial auction problem as in de Vries and Vohra (2003), which we adopt and extend to include the ask price condition.

Let  $C$  be the set of bidders (or carriers),  $P \subseteq R$  the set of requests called auction pool and  $B$  the set of offered bundles, which is a subset of all possible bundles (i.e.,  $B \subseteq 2^P$ ). Please note that bundle  $B \subset R$  consists of several requests that we designate with  $r \in B$ . The value of a bid for bundle  $B \in B$  of bidder  $c \in C$  is described by  $b_{c,B}$ . Variable  $y_{c,B}$  defines if  $B$  is allocated to  $c$  ( $y_{c,B} = 1$ ) or not ( $y_{c,B} = 0$ ). Suppose that the ask price of seller (or carrier)  $c \in C$  for his released requests  $\mathcal{R}_c \setminus \mathcal{R}'_c$  is  $a_c$ , which corresponds to the profit loss that carrier  $c$  will obtain for releasing these requests. The Combinatorial Auction Problem associated with the WDP has the following form:

$$\max \sum_{c \in C} \sum_{B \in B} b_{c,B} y_{c,B} \quad (2)$$

$$\text{s. t.} \quad \sum_{B \in B} y_{c,B} \leq 1 \quad \forall c \in C \quad (3)$$

$$\sum_{c \in C} \sum_{B \ni r} y_{c,B} = 1 \quad \forall r \in P \quad (4)$$

$$\sum_{c \in C} \sum_{B \in B} b_{c,B} y_{c,B} \geq \sum_{c \in C} a_c \quad (5)$$

$$y_{c,B} \in \{0, 1\} \quad \forall c \in C, B \in B. \quad (6)$$

The objective function (2) to be maximized determines the sum of bids for bundles assigned to carriers. Each carrier  $c$  gets at most one bundle  $B$  (cf. constraints (3)) and each request  $r$  is assigned to each allocated bundle exactly once (cf. constraints (4)). This formulation differs from de Vries and Vohra (2003) due to the fact that all requests are supposed to be allocated (i.e., we use an equation instead of a “less or equal” formulation in (4)). We follow this approach, since otherwise requests/bundles may remain unassigned. Non-allocated requests would revert back to the original carrier and might not be

able to be served due to capacity restrictions (cf. Gansterer and Hartl, 2016a). Please note that the reformulation also means that the auction's efficiency (cf. Section 2.1) is not necessarily achieved (perhaps a better solution would be possible with slack in (4)). For the participating carriers, however, the individual rationality is more important, which is guaranteed with the model (in particular with constraints (5)). The profit from the auction has to be greater than the minimum value each seller wants to receive.

The considered CAP is embedded in the collaborative framework and solved by ILOG Cplex to optimality. After the optimal bundle allocation has been found, the payment for each winning carrier has to be set, which is done by Eq. (7).

$$p_{c,B} = \begin{cases} b_{c,B} & \text{if } c \text{ wins bundle } B \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

Since each carrier is associated with at most one bundle  $B$ , the price a carrier has to pay  $p_c = \sum_{B \in B} p_{c,B}$  as well as the price which has to be paid for a bundle  $p_B = \sum_{c \in C} p_{c,B}$  is unique. Hence, we sometimes drop the index  $c$  or  $B$  for a better comprehension depending on the situation.

**Step (v): Profit allocation.** Finally, the profit of the auction  $\sum_{c \in C} p_c$  has to be allocated to the participating carriers. Thereby both, *budget balancing* and *individual rationality*, must be taken into account, as dissimilarities of the exchanged requests have to be balanced between the carriers. In order to provide individual rationality, first each carrier gets his ask price  $a_c$ , i. e.,  $\sum_{c \in C} (p_c - a_c)$  has to be allocated afterwards. Since classical allocation approaches from cooperative game theory, e. g., shapley value or nucleolus (cf. Liu et al., 2010), are not applicable due to the information available, custom allocation techniques must be developed.

Based on preliminary investigations, we develop and apply a new bundle oriented approach: For each allocated bundle  $B$ , a price  $p_B$  is identified associated with a carrier  $c$  according equation (7). This price determines the quality of a bundle for the corresponding carrier. Thus, we define a fair profit allocation  $\pi_c$  to carrier  $c$  in such a way that the carriers involved in an attractive bundle regarding their released requests, i. e., with respect to the value  $p_B$ , obtain a higher profit-sharing. Therefore, we allocate a share of the price  $p_B$  for each bundle  $B$  according to the revenue a carrier  $c$  has contributed to bundle  $B$ . This results in the following profit allocation:

$$\pi_{c,B} = \frac{\sum_{r \in B} \chi_{r,c} \rho_r}{\sum_{r \in B} \rho_r} \cdot \frac{\sum_{\tilde{c} \in C} (p_{\tilde{c}} - a_{\tilde{c}})}{\sum_{\tilde{c} \in C} p_{\tilde{c}}} \cdot p_B \quad \forall c \in C, B \in B. \quad (8)$$

Please note that  $\rho_r$  determines the revenue of a request  $r \in R$  coming originally from carrier  $c \in C$  if and only if the binary allocation parameter holds  $\chi_{r,c} = 1$ . This revenue is specified by the route's length of carrier  $c$  serving only request  $r$  (cf. Eq. (17)). The first term of the product in (8) specifies the ratio of revenue that has been submitted to the bundle  $B$  by carrier  $c$ . The fact that exactly the residual of the auction prices  $\sum_{c \in C} (p_c - a_c)$  is allocated, is provided by the second term, while the last term holds that the price of a bundle  $p_B$  is distributed.

To achieve the profit allocation of carrier  $c$  (over all bundles), the values of Eq. (8) has to be summed up over all bundles  $B \in B$  and added to the ask price, i. e.,

$$\pi_c = a_c + \sum_{B \in B} \pi_{c,B}. \quad (9)$$

Since each carrier  $c$  gets at least his ask price  $a_c$ , i. e.,  $\pi_c \geq a_c$  for all  $c \in C$ , the developed profit allocation is individual rational. It is shown in the following that (9) satisfies  $\sum_{c \in C} \pi_c = \sum_{c \in C} p_c$ , thus, the method is budget balanced.

$$\sum_{c \in C} \pi_c \stackrel{(9)}{=} \sum_{c \in C} \left( a_c + \sum_{B \in B} \pi_{c,B} \right)$$

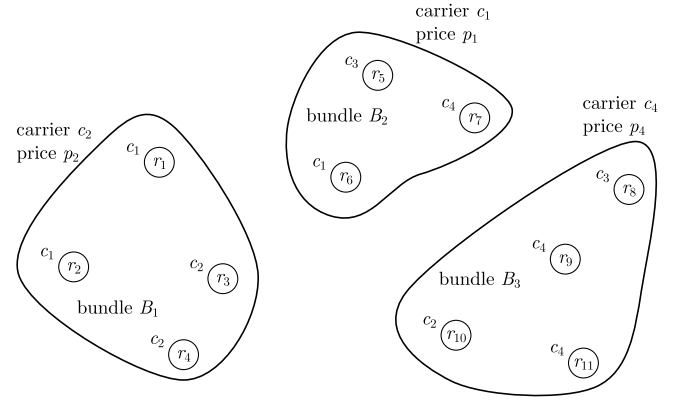


Fig. 4. Bundle-wise profit allocation with respect of the participating carrier's revenue.

$$\begin{aligned} & \stackrel{(8)}{=} \sum_{c \in C} \left( a_c + \frac{\sum_{r \in B} \chi_{r,c} \rho_r}{\sum_{r \in B} \rho_r} \cdot \frac{\sum_{\tilde{c} \in C} (p_{\tilde{c}} - a_{\tilde{c}})}{\sum_{\tilde{c} \in C} p_{\tilde{c}}} \cdot p_B \right) \\ & = \sum_{c \in C} a_c + \frac{\sum_{\tilde{c} \in C} (p_{\tilde{c}} - a_{\tilde{c}})}{\sum_{\tilde{c} \in C} p_{\tilde{c}}} \cdot \sum_{B \in B} \frac{p_B}{\sum_{r \in B} \rho_r} \cdot \sum_{r \in B} \rho_r \underbrace{\sum_{c \in C} \chi_{r,c}}_{=1} \\ & = \sum_{c \in C} a_c + \frac{\sum_{c \in C} (p_c - a_c)}{\sum_{c \in C} p_c} \cdot \underbrace{\sum_{B \in B} p_B}_{=\sum_{c \in C} p_c} \\ & = \sum_{c \in C} a_c + \sum_{c \in C} (p_c - a_c) = \sum_{c \in C} p_c \end{aligned}$$

In Fig. 4, the bundle-wise profit allocation method of Eqs. (8) and (9) is displayed with an example of three bundles and four carriers. In the way the profit allocation is done the price  $p_2$  of bundle  $B_1$  paid by carrier  $c_2$  will be allocated to carriers  $c_1$  and  $c_2$ , taking into account their request's revenue submitted to the bundle (cf. Fig. 4). Since the carriers  $c_3$  and  $c_4$  are not involved in the bundle  $B_1$  due to their requests submitted to the auction pool, the nominator of the first fraction in (8) will be zero for  $c_3$  and  $c_4$ . Moreover, if the proportion of revenue contributed to the bundle by  $c_1$  is very high (relatively to  $c_2$ ), this will be rewarded through the first term of the product in  $\pi_{c,B}$ . Additionally, if  $B_1$  is very suitable for  $c_2$ , the valuation of the bundle represented by  $p_2$  is relatively high, which increases the profit allocation value  $\pi_{c,B_1}$  for  $c_1$  and  $c_2$ .

## 5. The bundle selection problem

The bundle selection problem requires identifying bundles of requests that carriers can bid on. Since bidding on all  $2^p - 1$  possible bundles from an auction pool of size  $p$  is not reasonable for carriers, the number of bundles (step (iii)) must be reduced (cf. Gansterer and Hartl, 2018a). In addition, limiting the number of bundles is a natural part of auction design (cf. Pekeć and Rothkopf, 2003). This can be done, for example, by defining an appropriate bidding language (cf. Bichler et al., 2011), which implies in this context whether the bundles are built by the carriers or the auctioneer. Considering that Berger and Bierwirth (2010), Schopka (2018) and Gansterer et al. (2020) have shown for similar collaboration approaches that the outcome of the auction is better when the auctioneer generates the bundles, we also follow this approach. It is worth mentioning that creating bundles by the carriers (bidders) can also lead to good results. However, the auction mechanism has been designed in a suitable way, e. g., a combination of iterative multi-round and combinatorial auction as in Chen (2016).

The selection of sufficiently *attractive* bundles offered in the auction process (cf. step (ii)) is a difficult task for the auctioneer due to incomplete information. Hence, such an auction can never be completely

neutral (cf. Pekeč and Rothkopf, 2003). On the other hand, the bundle selection has the biggest influence on the collaboration's outcome as well as the efficiency of the auction. Thus, this process can be seen as the “heart” of the entire collaboration procedure. The quality of this step gives a natural incentive whether to join a cooperation or not. The *attractiveness* of a bundle depends primarily on the valuation of the carriers, which is only determined once the bundles to be bid on are known. Thus, the selection of sufficiently suitable bundles is a *stochastic optimization problem*, known as Bundle Selection Problem (cf. Gansterer and Hartl, 2018a), whose formulation is introduced in detail in the following. Please note that all notations used in this section with respect to sets, parameters or variables are given in Table 3.

Let  $\Xi_{c,B}$  be the stochastic distribution of bids for bundle  $B \in \mathcal{B}$  from carrier  $c \in \mathcal{C}$ . The distribution depends on  $B$  and  $c$ , because the interdependence between the carrier's hidden customer data and the request information of a bundle affects the bid of  $c$  for  $B$ . Moreover,  $\sigma \in \mathcal{S}$  describes a scenario of bundles that are supposed to be allocated and  $\kappa$  is an upper bound of bundles to be selected. As in the WDP (cf. Section 4), the decision variable  $y_{c,B}$  specifies the allocation between carrier  $c$  and bundle  $B$ . Then, the BuSP can be formulated mathematically as follows:

$$\max_{\sigma \in \mathcal{S}} \quad \mathbb{E}^\sigma \left( \max_{c \in \mathcal{C}} \sum_{B \in \mathcal{B}_\sigma} \Xi_{c,B} y_{c,B} \right) \quad (10)$$

$$\text{s. t.} \quad \sum_{B \in \mathcal{B}_\sigma} y_{c,B} \leq 1 \quad \forall c \in \mathcal{C}, \sigma \in \mathcal{S} \quad (11)$$

$$\sum_{c \in \mathcal{C}} \sum_{B \ni r: B \in \mathcal{B}_\sigma} y_{c,B} = 1 \quad \forall r \in \mathcal{P}, \sigma \in \mathcal{S} \quad (12)$$

$$\sum_{c \in \mathcal{C}} \sum_{\sigma \in \mathcal{S}} \sum_{B \in \mathcal{B}_\sigma} y_{c,B} \leq \kappa \quad (13)$$

$$y_{c,B} \in \{0, 1\} \quad \forall c \in \mathcal{C}, B \in \mathcal{B}_\sigma \quad (14)$$

The objective function (10) determines the expected value of the stochastically modelled bids over all possible scenarios  $\sigma$ , which is to be maximized. Constraints (11), (12) and (14) must be fulfilled, as it was the case in the WDP. Condition (13) models that at most a formerly fixed number  $\kappa$  of bundles in total is allocated over all scenarios  $\sigma \in \mathcal{S}$ .

Since the only stochastic variable in this optimization problem is represented by the bids, a robust optimization technique must be applied in order to predict them well (cf. Shapiro et al., 2009). For this purpose, a scenario-based approach is presented in which different scenarios with different possible bids for the bundles are run (cf. Section 5.1). In order to apply only a relatively small number of reasonable bundles in the scenario-based approach, pre-selection techniques have to be developed to reduce the number of bundles. In this paper, two pre-selection techniques are implemented and compared. In the *cluster-based* (see Section 5.2) and in the *neural network-based* (cf. Section 5.3) approach, machine learning methods are utilized, which has not been studied in the literature so far. In particular, the use of machine learning methods is mandatory in order to achieve reasonable results due to the complex collaborative setting (cf. Gansterer and Hartl, 2020).

### 5.1. Scenario-based bundle reduction approach

The scenario-based bundle reduction approach builds several scenarios in which the bids for solving the BuSP are approximately determined by a stochastically distributed bid-proxy. In order to create such a bid-proxy, a measure to indicate the attractiveness for a bundle has to be developed (cf. Section 5.1.1). This attractiveness measure is used in order to approximate bids stochastically by an appropriate distribution (cf. Section 5.1.2).

#### 5.1.1. Attractiveness measure of a bundle

The attractiveness of a bundle (or more general of a set of points with certain features) can be defined in several ways depending on the problem considered. In this paper, we developed an attractiveness measure specified by commonly known attributes that might have an impact on the real bid of a carrier, such as:

- density  $\delta_B$  of bundle  $B$ ,
- number of vehicles  $v_B$  and length of routes  $l_B$  needed for serving the requests within bundle  $B$ ,
- distances from locations in bundle  $B$  to each carrier's depot  $d_c$ , i. e., the value  $\text{dist}(B, d_c)$ , as well as
- total revenue  $\sum_{r \in B} \rho_r$  of bundle  $B$  and number of requests within a bundle  $|B|$ .

The density  $\delta_B$  is identified by the weighted sum of direct travel distances  $t_r = \text{dist}(p_r, d_r)$  for request  $r$  divided by the maximum distance between the requests and the bundle's centroid  $c_B$ , i. e.,  $\text{dist}(r, c_B)$ . This distance is determined through the sum of distances of pickup and delivery locations to  $c_B$ . The weights for the direct travel distances  $t_r$  equal  $\text{dist}(r, c_B)$ , i. e.,

$$\delta_B = \frac{\sum_{r \in B} \frac{t_r}{\text{dist}(r, c_B)}}{\max_{r \in B} \text{dist}(r, c_B)} \in (0, 1) \quad \text{with} \quad c_B = \frac{\sum_{r \in B} t_r \cdot \text{centroid}_r}{\sum_{r \in B} t_r},$$

while the centroid of a request  $\text{centroid}_r$  is defined as the midpoint on the line between pickup and delivery node. In order to identify the number  $v_B$  of routes and the length  $l_B$  for bundle  $B$ , an artificial depot is located at  $c_B$  and a double insertion heuristic is applied, where the time windows are considered to generate a vehicle routing solution for the requests included in  $B$  served from the artificial depot. The distance  $\text{dist}(B, d_c)$  between bundle  $B$  and depot  $d_c$  is calculated as the sum of distances between all pickup locations and depot as well as all delivery locations and depot.

Each assessed impact of the attractiveness measure has to be weighted such that the influences are normalized which is done by the exponents in the product of Eq. (15). To summarize, the valuation of attractiveness of bundle  $B$  for carrier  $c$  is modelled as

$$\eta_{c,B} = \frac{(\sum_{r \in B} \rho_r)^\alpha |B|^\beta (v_B)^\gamma (\delta_B)^\mu}{(l_B)^\nu \text{dist}(B, d_c)^\tau}, \quad \alpha, \beta, \gamma, \mu, \nu, \tau \in \mathbb{R}^{\geq 0}. \quad (15)$$

Contrary to the similar concept of the proxy in Gansterer and Hartl (2018a), the attractiveness measure  $\eta_{c,B}$  is modelled in a different way, since additional information on time windows or vehicle capacities has to be considered here. The measure's structure in Eq. (15) is chosen in this manner, because intuitively the sum of profits  $\rho_r$  and the number of requests  $|B|$  included in a bundle are supposed to have a positive influence on the attractiveness of a bundle. Thus, these values are listed in the numerator. Additionally, a dense bundle  $\delta_B$  seems to be a good one due to small travel distances. The number of vehicles  $v_B$  needed with respect to the customers' time windows should also affect the attractiveness positively, since the carriers usually look for single requests that fit into scheduled routes with free capacity and not for bundles of requests that have to be served together on one new vehicle. Intuitively, the length of the route within a bundle  $l_B$  and the sum of request distances to the depot  $\text{dist}(B, d_c)$  are supposed to have a negative effect on  $\eta_{c,B}$ , hence, these values are assigned to the denominator.

Preliminary studies have shown that the best combination of weights is  $(\alpha, \beta, \gamma, \mu, \nu, \tau) = (0.15, 1.8, 0.2, 0, 0, 1.5)$ . It can be noticed that density has no impact on the attractiveness of a bundle. The reason for this is that density does not take time window information into account, which is an important relationship between requests, and that a dense bundle does not have a preferred L- or U-shape, which can be easily integrated into existing routing solutions as these are requests located around a depot (cf. L-shape in Fig. 9). Additionally, since the shuttle-tour distances are included in  $\text{dist}(B, d_c)$ , the potential length of a tour



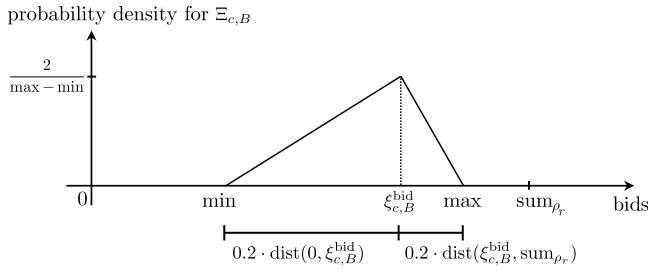


Fig. 5. Triangle distribution  $\Xi_{c,B}$  for an approximated bid  $\xi_{c,B}^{bid}$ .

within a bundle  $I_B$  also seems to have no influence on the attractiveness of a bundle. Nevertheless, these key values are still included, since the bundle reduction approach is also supposed to be applicable on different data structures, where density or tour length might have an impact. In order to find the weights of influence for  $\eta_{c,B}$  in differently structured data, e. g., a Bayesian Optimization approach can be used for the parameter tuning (cf. Roman et al., 2016). The number of vehicles needed has a very large impact, as the time windows are considered in the determination.

In the following subsection, the introduced attractiveness measure is used to build a triangle distribution which represents a bid-proxy. With such a distribution, bids can be generated that are supposed to reflect the real bid of a carrier for the bundle taken into account.

#### 5.1.2. Stochastic triangle distribution as a bid-proxy

After all bundles are valued by means of Eq. (15), the bundle selection has to be carried out with respect to the BuSP. Since the attractiveness value  $\eta_{c,B}$  is only an approximation and the bids for various bundles can be located in different bid ranges, each bundle's attractiveness has to be mapped on the range of its minimum and maximum possible bid  $[b_{\min}^B, b_{\max}^B]$ . This is done through an affine mapping, while  $\eta_{\min} = \min_{c \in C, B \in B} \{\eta_{c,B}\}$  and  $\eta_{\max} = \max_{c \in C, B \in B} \{\eta_{c,B}\}$ , i. e.,

$$f: [\eta_{\min}, \eta_{\max}] \rightarrow [b_{\min}^B, b_{\max}^B],$$

$$\xi_{c,B}^{bid} = f(\eta_{c,B}) = \frac{b_{\min}^B - b_{\max}^B}{\eta_{\min} - \eta_{\max}} \eta_{c,B} - \frac{b_{\min}^B \eta_{\max} - b_{\max}^B \eta_{\min}}{\eta_{\min} - \eta_{\max}} \quad \forall c \in C, B \in B.$$

In order to reduce approximation errors and to achieve a robust solution for the BuSP, triangular distributions  $\Xi_{c,B}$  are created by using the approximated bids  $\xi_{c,B}^{bid}$  to estimate the bids for a bundle  $B$  given from carrier  $c$ . For this purpose,  $\xi_{c,B}^{bid}$  is taken as mode, while the lower limit can be set to zero and the upper limit to the sum of revenues for bundle  $B$ , i. e.,  $\sum_{r \in B} \rho_r$ . However, this will result in a very flat triangle that behaves like a uniform distribution due to a wide definition range  $[b_{\min}^B, b_{\max}^B]$ . Since we want the attractiveness value to affect the selection of sufficiently good bundles but also let the selection keep its probabilistic behaviour, the right size of the definition range of  $\Xi_{c,B}$  is of crucial importance. Preliminary studies have shown that 20% of the entire value range is a good measure for defining the width of the triangular distribution to maintain the desired properties described before (cf. Fig. 5).

In the scenario-based approach, we randomly draw a bid for each bundle  $B$  and carrier  $c$  with the created triangle distribution  $\Xi_{c,B}$ , which is called a scenario. Hence, an approximated bid matrix is generated in each scenario that is used to solve the WDP without constraint (5). In this way, the best bundle allocation is found, holding all assignment conditions. If this procedure is repeated sufficiently often, frequently assigned bundles can be identified. These bundles represent the most promising ones for allocation. Hence, they are offered by the auctioneer during the bidding process.

Please recall that the number of possible bundles which can be generated out of  $p$  requests is increasing exponentially with the number

of requests within the auction pool  $\mathcal{P}$ . This explains why the valuation of the attractiveness  $\eta_{c,B}$  for all create-able bundles is not possible. Thus, a clever pre-selection approach must be applied to find bundles with potentially good attractiveness. For this purpose, we use a *k-means cluster-based approach* as well as a deep feed forward *neural network approach*. Please remark that both approaches are not used in their original intention for which they were developed, but as tools to *weakly classify* a request to a bundle in order to generate multiple different and sufficiently diversified bundles for the scenario-based bundle reduction approach described in this section. Both pre-selection techniques create a probability matrix that measures how likely a request shall be assigned to a certain bundle (cf. cluster-based, Section 5.2) or carrier (cf. neural network-based, Section 5.3). In order to create bundles for the scenario-based reduction approach, this probability matrix is used for assigning the requests to bundles randomly with respect to the discrete distribution described by the matrix.

#### 5.2. Cluster-based pre-selection of bundles

As we need to find a good pre-selection of bundles, which are disjoint to each other in a bundle solution, a *clustering* partitioning method such as *k-means* is a useful approach (cf. Rokach, 2009). However, before implementing *k-means*, the number of clusters to be generated has to be defined. Here, this is equivalent to the knowledge of the number of bundles leading to the best outcome of the auction, which is only revealed after the bidding process.

A clever strategy is to apply *k-means*  $n^c$  times; each time with different number of clusters  $k$  in order to create several bundles. To obtain reasonable clusters,  $k$  is randomly drawn uniformly distributed within the boundaries of

$$k_{\min} = \frac{|C|}{2}, \quad k_{\max} = \max \left\{ \left\lceil \frac{|\mathcal{P}|}{2.5} \right\rceil, k_{\min} \right\}.$$

The lower bound  $k_{\min}$  is chosen, because bundles with too many requests are not suitable for the carriers due to the applicability, i. e., with the size of the bundle, the probability increases that a bundle consists of a combination of requests that no carrier is able to serve. Furthermore, if the bundle sizes get too small (which comes along with many clusters), the bundles will be unattractive for the carriers, which explains the choice of  $k_{\max}$ .

In order to determine a similarity measure of requests to clusters, the location of pickup and delivery customers are taken into account, while euclidean distance is applied within the *k-means* approach. For this reason, a request is represented as a vector  $(x_p, y_p, x_d, y_d) \in \mathbb{R}^4$ . Since there is no intuitive measure for calculating the “distances” between other request features, e. g., time windows, revenues etc., we omit them in the *k-means* approach. Moreover, the (ordered) feature vector  $(x_p, y_p, x_d, y_d)$  describes a direction within the space  $\mathbb{R}^4$  that is irrelevant in clustering of the requests, as it implies an order in which the requests are served that cannot be checked to feasibility within the clustering approach, and thus, only occurs during bidding on the requests. In Fig. 6, different distance values are depicted between two requests,  $(x_{p_1}, y_{p_1}, x_{d_1}, y_{d_1})$  and  $(x_{p_2}, y_{p_2}, x_{d_2}, y_{d_2})$ . The left hand side shows the distance of the requests considered for the fixed order, i. e., the feature vector always contains the pickup coordinates first and the delivery coordinates second. In contrast, the right hand side displays the distance of the two feature vectors in lexicographical order with respect to the  $x$  and  $y$  values being compared to each other. It can be seen that the two requests in Fig. 6 might be a *good* cluster, since without knowing capacity or time windows, the order  $(p_1, p_2, d_1, d_2)$  can possibly be a feasible sequence. A good cluster can be specified as a size-balanced cluster with pairwise small distances of pickup and delivery nodes to each other. However, in the first case (see left hand side in Fig. 6), the requests would not be considered as a cluster because of the large distance. In the last case (see right hand side in

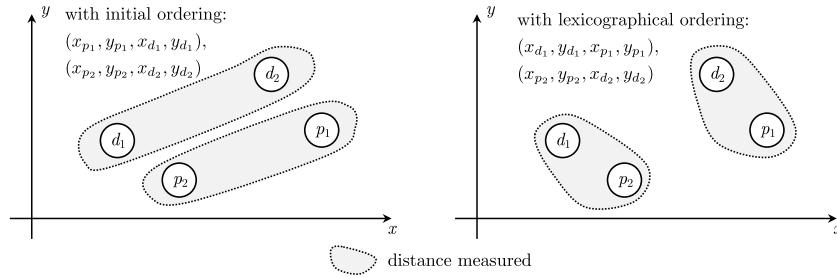


Fig. 6. Different distances measured when ordering pickup and delivery lexicographically or not.

Fig. 6) it appears that the requests can form a good cluster. To avoid this problem, and consequently, to associate also pickup with delivery nodes, we first apply lexicographical ordering on each vector before performing  $k$ -means. In particular, vector  $(x_p, y_p, x_d, y_d)$  describes the same request as vector  $(x_d, y_d, x_p, y_p)$ .

When a run of  $k$ -means with a randomly fixed  $k$  is finished, the calculated cluster centres are taken for measuring how likely a request is assigned to each centre, i.e., for calculating the probability matrix described above. As mentioned at the end of Section 5.1, we do not use  $k$ -means in its original intention, i.e., the clusters determined by  $k$ -means for defining the request bundles. Here, we use the so-found cluster centres for a fuzzy classification criterion in order to receive several bundle constellations through a weak request to cluster centre assignment. A probability matrix for assigning request  $r$  to cluster  $C$  with respect to the similarity measure is determined by

$$\text{Prob}(r, C) = \frac{\text{sim}(r, C)}{\sum_C \text{sim}(r, C)}, \quad \text{sim}(r, C) = (\text{dist}(r, C) + 1)^{-1}. \quad (16)$$

In (16), the operator  $\text{dist}(r, C)$  describes the distance of request  $r$  to the considered cluster  $C$  as the distance of  $r$  to the cluster centre. Hence,  $\text{dist}(r, C)$  can be interpreted as the dissimilarity of request  $r$  to cluster  $C$ , the reciprocal value  $\text{sim}(r, C)$  describes the corresponding similarity. Additionally, we added some value in the denominator such that division by zero is prevented. Altogether,  $\text{Prob}(r, C)$  depicts the relative similarity of  $r$  to  $C$ , thus a kind of probability. Using the probability matrix (16) as a discrete distribution, the assignment of request  $r$  to cluster  $C$  is done  $n^a$  times. To avoid multiple classes or bundles with identical requests, we provide a unique index for each class or bundle, respectively.

Since this procedure is repeated multiple times, we generate a vast variability within the bundles given to the bundle reduction process, while the computational complexity is manageable. For example,  $n^c = 40$  and  $n^a = 25$  leads to over 2,000 bundles that must be evaluated and reduced by the scenario-based approach solving the BuSP described in Section 5.1.

As the cluster-based pre-selection does only take customer locations into account, it can be seen as a intuitive first pre-selection method for the considered problem. However, since the customer data of each carrier stays unrevealed and the suitability of a bundle for a carrier strongly depends on this hidden customer data, it is not purposeful to develop similarity measures for other attributes, e.g., time windows, as we do not know whether similar or complementary time windows of requests within a bundle are compatible for a carrier. Still it is worth investigating whether time windows or demands are supposed to be used in the pre-selection process without developing various distance measures. In addition, applying machine learning methods within the auction-based exchange mechanism is of interest to investigate (Gansterer and Hartl, 2020). Hence, a neural network based approach for pre-selecting bundles that takes all request attributes into account is introduced in Section 5.3, which may learn (non-linear) relations between the request attributes and the carriers.

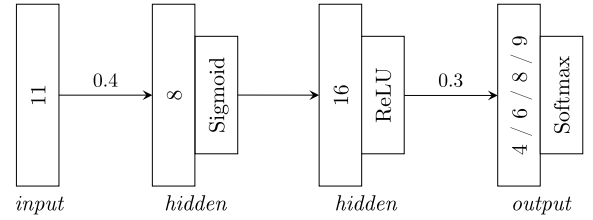


Fig. 7. Deep feed forward neural network architecture for request to carrier classification.

### 5.3. Neural network approach for pre-selection

The principal task for the auctioneer is to evaluate, which carrier is supposed to get which requests. Hence, the bundle selection problem can also be regarded as *classification* problem. For identifying the best classes in the pre-selection process, various classification algorithms can be used (cf. Narayanan et al., 2017). Particularly, *neural networks* have shown promising results solving classification problems (cf. Zhang, 2000), especially for the kind of problem at hand. Here, requests with certain attributes have to be assigned to specific carriers. Neural networks are universal function estimators for recognizing patterns. In their proceeding, they are similar to the human brain. Considering a supervised learning setting, neural networks can approximate a function which is able to identify different classes in given data (cf. Aggarwal, 2018). Thus, a neural network can approximate the distance measure between features such as revenues or even time windows, which cannot be calculated intuitively (cf. Section 5.2). In our approach, a deep feed forward neural network (DFNN) is implemented in order to learn which requests are supposed to be assigned to which carrier. As mentioned at the end of Section 5.1, we do not use the classification result of the neural network as fixed request-carrier-assignment. It is used as a weak classification for determining random assignment of a request to a certain bundle by using a probability matrix defining the likelihood of a request-carrier-assignment derived from the neural network.

To train the network, training data has to be generated from the function that needs to be approximated with the correct classifications for the data. This is provided by the centralized cooperative solution of artificial cooperation data sets, which are generated according to the auction pool data known by the auctioneer (cf. Section 6.2). A part of this data (33%) is used as test data to evaluate the loss of the trained network. In addition, the network architecture has to be defined for the specific problem. A larger network would lead to overfitting, whereas a smaller network would lead to underfitting on the training data. Also, other characteristics such as (non-)linearity have an impact on overfitting (cf. Aggarwal, 2018). Therefore, the network architecture is carefully chosen, based on previous empirical investigations (cf. Fig. 7).

Since the input is a request to be classified, the number of features and thus of input neurons equals 11. Each request has 11 features in particular:  $(x, y)$  locations for pickup and delivery, beginning and end

of time windows at pickup and delivery location, duration of service, demand and revenue. We provide two different DFNN depending on the number of carriers participating in the cooperation network. This can be seen in the number of output neurons (4 or 6 carriers). In general, the neural network has two dense hidden layers with 8 and 16 neurons. Each neuron is connected to each neuron of the subsequent layer. In order to ensure non-linearity within the network, different techniques can be applied. A rather simple but effective method is to drop information between layers (cf. [Srivastava et al., 2014](#)). So, we use a dropout before the first hidden layer (with 40%) and after the second hidden layer (with 30%). Additionally, we include non-linear activation functions after the first (Sigmoid) and the second (Rectified Linear Unit, ReLU) layer on the neuron's signal, given by

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}} \quad \text{and} \quad \text{ReLU}(x) = \max\{0, x\}.$$

Looking at the output signal, a softmax activation is utilized in order to obtain classification scores in the range of  $[0, 1]$  ensuring that the sum of them equals one. Hence, the results represent a probability of class association. Finally, cross entropy is defined as loss function so that the neural network can backpropagate the gradients of this loss during the learning process.

Once the DFNN has been trained, the auctioneer can determine a probability matrix for the assignment of each request in the auction pool to the carriers through calculating the softmax vector for each request. This probability matrix is used for drawing requests randomly to carrier assignments (similar to the cluster-based approach) on which the scenario-based bundle reduction is applied. The random drawing is considered  $\tilde{n}^a$  times to create several bundles.

Please note that the proposed technique does not learn any dependencies between the requests within the auction pool, since each request is presented individually to the DFNN. However, this might be an advantage, as learning dependencies can have impacts like *overfitting the request bundles*. Requests that fit well together (probably on one vehicle) do not necessarily have to be attractive to carriers that often search for several single requests for routes already planned. Consequently, the real valuation of a bundle strongly depends on the part of customer data that is not revealed to the auctioneer and thus this valuation cannot be learned.

## 6. Evaluation

In this section, we present the results of the evaluation of the auction-based framework for the collaborative PDPTWHV. Therefore, we generate suitable data sets (cf. Section 6.1). The outcomes of the cooperation, which are determined with our framework, can be evaluated with an upper and lower threshold. The lower threshold is obtained when all carriers individually optimize their vehicle routing solution, while the upper threshold is estimated by a central transportation planning carried out by a central entity (cf. Section 2.1). The profit of decentralized cooperation cannot exceed the two bounds, as [Fig. 8](#) shows. The exact individual vehicle routing solution consumes many resources and time (if it can be calculated at all), which is why the generally better solution of cooperative planning provides a higher overall benefit (cf. Section 6.2). Please note that the exact solutions in individual as well as centralized planning are rather a conceptual solution and cannot be calculated for the underlying routing problem in most of the cases due to the complexity of the problem (which is  $\mathcal{NP}$ -hard) as well as the size of the instances.

### 6.1. Data generation

For evaluating our framework, we generate data sets based on the well-known PDPTW benchmark of [Li and Lim \(2001\)](#) that is available via ([SINTEF, 2008](#)). The data sets are organized in three classes lc, lr

and lrc that describe whether the customer nodes are clustered (lc), randomly distributed (lr) or partially clustered and partially distributed randomly (lrc) on the plane. The benchmark also differs in terms of vehicle capacities and length of time windows. In particular, data sets with small time windows and small vehicle capacities (1xx) as well as others with large time windows and large capacities (2xx) are considered.

In our application, we assume heterogeneous vehicles. Therefore, the existing capacities are changed randomly. For this purpose, 25% of the vehicles are reduced by 30% of their original capacity, 25% of the vehicles are increased by 30%, and the rest of the vehicles remains unchanged. The fixed costs for a vehicle are determined depending on the capacity. Furthermore, a revenue  $\rho_r$  for request  $r$  is added to the data. Thereby, we use the variable costs resulting from the length  $\text{len}(r)$  of a shuttle-tour serving  $r$  and starting from the depot of the carrier who originally acquired the request. In practice, the largest share of the total costs is accounted for by personnel, which corresponds to the duration and thus the length of a tour. It is weighted with the variable cost factor  $c_{\text{var}}$  and a certain factor  $\rho_{\text{var}}$  indicating the required size of the buffer for achieving a profit. Here, the variable cost parameter is  $c_{\text{var}} = 1$ . Since the profit margin in practice is about 5%, we consequently choose  $\rho_{\text{var}} = 1.05$ .

$$\rho_r = \rho_{\text{var}} c_{\text{var}} \text{len}(r). \quad (17)$$

In order to generate multi-depot instances from the heterogeneous single depot instances, four, six, eight or nine instances are distributed over the plane in such a way that their business areas overlap slightly. The structure of the instances created is shown in [Fig. 9](#). Since the benchmark of [Li and Lim \(2001\)](#) contains approximately 50 requests (i. e., 100 nodes) per depot, the number of customers were randomly reduced, such that there are problem instances with 20, 25 or 30 requests per depot. In this way, 4-, 6-, 8- and 9-depot data sets are created containing 60 problem instances each, where the classes (lc, lr, lrc) are chosen with equal proportions. The data sets can be downloaded from [BWOR \(2020\)](#).

### 6.2. Results

In our performance analysis, we compare the cluster-based (CB) and the neural network-based (NN) pre-selection variant for the scenario-based bundle selection. To do so, the parameters of the decentralized collaboration framework are generally set as specified in [Table 4](#). The variants are evaluated on all generated instances (cf. Section 6.1), which are considered as planning periods for the collaboration network. The framework itself is implemented in C++ and executed multi-threaded (i. e., each carrier's calculations are done with a single thread) on a Windows Server with a 2.72 GHz CPU and 383 GB RAM.

For using the neural network-based pre-selection approach, 1,200 instances each with 4, 6, 8 as well as 9 depots were created with a data set generator implemented by the authors. These instances have different characteristics regarding, e. g., time window and capacity parameters (cf. [Rüther and Rieck, 2020](#)). The generated instances are divided into training and test data, while the latter represents 33% of the entire data. The trained networks have a final accuracy of 89% (4-depot), 90% (6-depot), 92% (8-depot) and 92% (9-depot) on the test data with respect to the correct classification. Please note that the networks need not to be trained to its best accuracy, since we do not use them for a precise request to bundle assignment but in a weak classification manner (cf. Section 5.3). Furthermore, the artificially generated data sets for training the neural network differ from the structure of the collaboration network instances, so that the neural network can also be applied on other instances distinguishing in, e. g., the carrier's customer data than the used data sets derived from [Li and Lim \(2001\)](#).

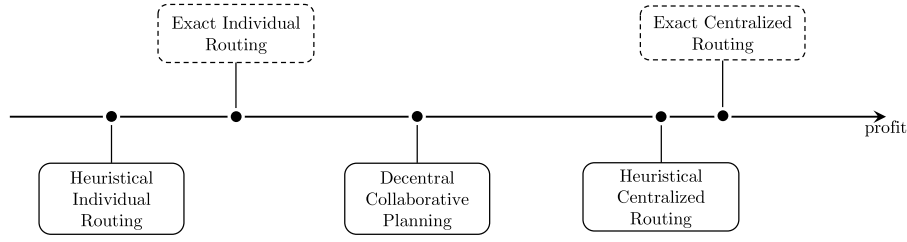


Fig. 8. Evaluation of auction-based framework's solution to individual and centralized cooperative planning; the dashed boxes containing the exact solutions are conceptual.

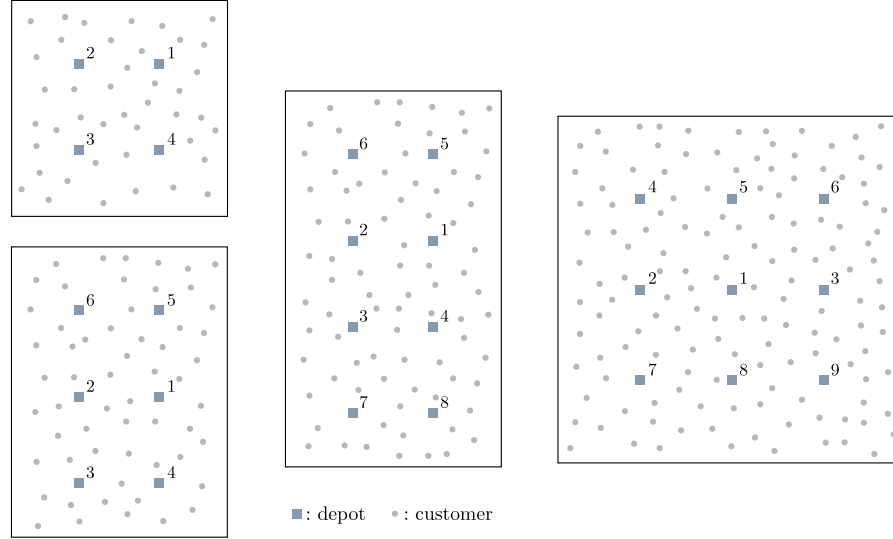


Fig. 9. Structure of generated data set of a collaboration network with 4, 6, 8 and 9 depots, where the regions of neighbouring depots overlap slightly.

In addition to the decentralized auction-based approaches, we consider both the individual and the centralized solutions as lower and upper thresholds, respectively (cf. Fig. 8). The individual and centralized transportation planning is heuristically solved by the Grouping GA introduced in Rüther and Rieck (2020) (cf. Section 3) while also applying the GA parameters given in Table 4. Moreover, these heuristical results are taken as initial solutions in order to calculate exact solutions for the (Multi-Depot) PDPTWHV with ILOG Cplex. To do so, a mathematical model formulation is implemented in GAMS and run on a Windows Server (2.72 GHz and 383 GB RAM) with 12 threads in parallel and an execution time limit of 2 h (7,200 s.). Please note that GAMS needs some time to set up the mathematical model, thus the time limits given for Cplex can be exceeded with respect to the entire execution (cf. Table 1).

In Table 1, the means of profits as well as of execution times for the considered transportation plannings regarding all 60 instances for each data set with 4, 6, 8 and 9 depots. Please note that the described profits are calculated for the entire collaboration network, i. e., the sum of all participating carriers within an instance are taken into account. Moreover, the mean, standard deviation, minimum and maximum of the relative profit improvement (RPI) regarding the heuristically solved individual solution is given. Thus, the impact of collaboration as a whole is compared to the individual and centralized planned solution (cf. Fig. 8). The RPI for a certain planning period, i. e., instance, is calculated through equation (18) regarding the ratio of collaborative profit  $\sum_{c \in C} \text{profit}(\tilde{\mathcal{R}}_c)$  and the initial profit  $\sum_{c \in C} \text{profit}(\mathcal{R}_c)$ , while  $\tilde{\mathcal{R}}_c$  describes the set of requests after collaboration, i. e.,

$$RPI = \frac{\sum_{c \in C} \text{profit}(\tilde{\mathcal{R}}_c)}{\sum_{c \in C} \text{profit}(\mathcal{R}_c)} - 1. \quad (18)$$

Based on the RPI in (18) for one instance, the mean as well as minimum and maximum are determined regularly over all instances.

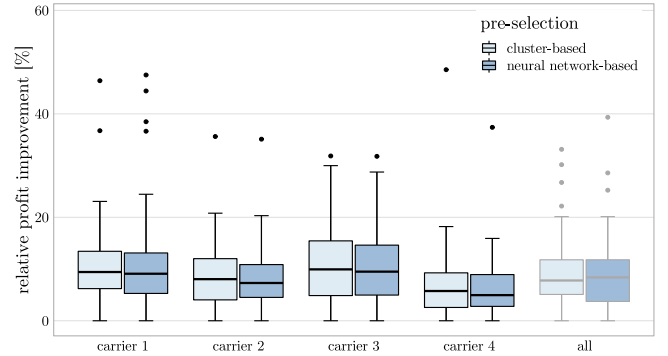


Fig. 10. Boxplot of rel. profit improvement in 60 periods for 4-depot collaboration network.

Please note that it is not reasonable to compare the bundle (pre-)selection of this contribution to results of formerly published bundle generation approaches, since the methods taken into account are suited particularly for the PDPTWHV. Thus, the additional attributes considered here, e. g. time windows, multiple and capacitated vehicles as well as heterogeneous fleets, might make our approaches rather inefficient for simpler TSPPC instances as investigated with respect to the auction-based exchange mechanism at hand in Berger and Bierwirth (2010) and Gansterer and Hartl (2016b, 2018a).

It can be seen that the improvement through the use of an exact solver for the individual routing is almost non-existent (0.27% at 4-depot, 0.14% at 6-depot, 0.18% at 8-depot and 0.14% at 9-depot), whereby the time limits (2 h) of the exact solver are exceeded for nearly every instance. The Grouping GA is up to 907 (9-depot) times faster,



**Table 1**

Average profit, mean, standard deviation as well as minimum and maximum of relative profit improvement (RPI) [%] and the execution time [sec.] over all 4-, 6-, 8- and 9-depot instances.

		Heuristical individual	Exact individual	Collaborative		Heuristical centralized	Exact centralized
				CB	NN		
4-depot	av. profit	3,193.42	3,196.01	3,455.43	3,413.23	3,603.06	3,610.87
	mean RPI	—	0.27	10.07	9.99	16.77	17.17
	min. RPI	—	0.02	0.20	0.47	2.77	2.77
	max. RPI	—	0.77	36.35	43.49	74.40	76.53
	exe. time	6.38	5,643.70	249.48	94.87	54.48	7,259.40
6-depot	av. profit	5,654.46	5,658.14	6,129.44	6,101.95	6,817.82	6,822.63
	mean RPI	—	0.14	10.17	10.34	18.92	19.01
	min. RPI	—	0.01	0.86	0.94	0.83	0.93
	max. RPI	—	0.72	42.69	34.83	190.22	190.22
	exe. time	7.88	6,125.58	542.04	180.43	157.48	7,228.80
8-depot	av. profit	7,404.62	7,410.29	8,041.33	8,098.62	8,314.63	8,320.84
	mean RPI	—	0.18	9.66	10.71	14.43	14.52
	min. RPI	—	0.00	0.60	1.05	1.28	1.28
	max. RPI	—	1.29	34.28	26.40	54.16	54.18
	exe. time	6.97	5,979.26	863.42	213.53	249.99	7,248.73
9-depot	av. profit	7,292.94	7,298.70	7,783.52	7,744.18	8,047.67	8,053.19
	mean RPI	—	0.14	7.41	6.82	12.19	12.27
	min. RPI	—	0.00	0.27	0.63	1.07	1.10
	max. RPI	—	0.69	18.97	18.90	32.66	32.66
	exe. time	6.19	5,614.32	856.91	217.13	250.94	7,253.18

while finding a sufficiently good solution (for all data sets). Please remember that the exact solver Cplex was executed with a warm start, i. e., the solution found by the GGA has been passed to Cplex as an initial solution that has to be improved. In doing so, 64 of the 240 single depot instances within the 4-depot, 78 of the 360 single depot instances within the 6-depot, 99 of the 480 single depot instances within the 8-depot and 149 of the 540 single depot instances within the 9-depot collaboration framework have been solved to optimality by Cplex. The relative gap of Cplex regarding the exact solution has been about 23% (4-depot), 25% (6-depot), 26% (8-depot) and 22% (9-depot) on average for all single depot instances. This is due to the complexity of the routing problem considered here. Consequently, this shows that the use of exact solvers for individual routing does not have a big impact on enhancing the transportation planning. Analogously, similar effects can be identified for the centralized transportation planning. Thereby, the exact solver does hardly improve the heuristically found initial solution (by 0.40% for 4-depot, 0.09% for 6-depot, 0.09% for 8-depot and 0.08% for 9-depot), while exhausting the time limit. As for the single depot instances, the GGA results have been used in Cplex for a warm start. Here, no multi-depot instance could be solved to optimality within the time limit. Moreover, the relative gap regarding the exact solution has been about 42% (4-depot), 48% (6-depot), 42% (8-depot) and 48% (9-depot) on average over all multi-depot instances. Hence, the GA's result represents a sufficiently good solution for centralized transportation planning, which is about 16.77% better for the 4-depot, 18.92% better for the 6-depot, 14.43% better for the 8-depot and 12.19% better for the 9-depot than the individually planned ones. Nevertheless, since centralized planning needs access to all customer data, these results can only be seen as a benchmark of our bundle selection approaches within the collaborative framework.

The scenario-based bundle selection approach with both of its variants, the cluster- and the neural network-based pre-selection, shows reasonable results with respect to the enhanced profit compared to the individual solution as well as the possible profit improvement given by the centralized planning approach. On average, the collaboration framework improves the overall profit by 10.07% for the 4-depot, by 10.17% for the 6-depot, by 9.66% for the 8-depot and by 7.41% for the 9-depot instances using cluster-based as well as by 9.99% for the 4-depot, by 10.34% for the 6-depot, by 10.71% for the 8-depot and by 6.82% for the 9-depot instances using neural network-based pre-selection. Both methods utilize over 52% of the cooperative potential

with respect to the profit improvement which is specified by (exact) centralized planning solution. In addition to the enhanced profit, the computational time is significantly smaller compared to the exact central solution. Since the neural network-based pre-selection reduces the number of offered bundle substantially compared to the cluster-based technique, it performs much faster with similar solution quality on average. In addition, considering more attributes than just the customer's locations may lead to slightly worse solutions, as dyssynergies regarding the unknown customer data of the carriers can be evoked more likely. Thus, the cluster-based approach determines a broader selection of bundles which are investigated with respect to problem specified attributes only in the next step, e. g., number of vehicles due to time windows, which can be derived from the gap between maximum RPIs of cluster- and neural network-based pre-selection for 6-depot instances in Table 1. It is worth mentioning that the neural network-based pre-selection achieves better results for the minimum RPI, which implies that considering other features than customer locations may improve the profit in more cases. To summarize, the collaboration approaches provide good solutions to optimize carrier's profit, while revealing as little information as possible.

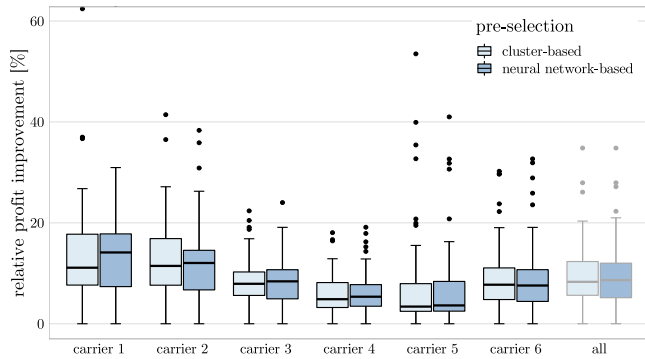
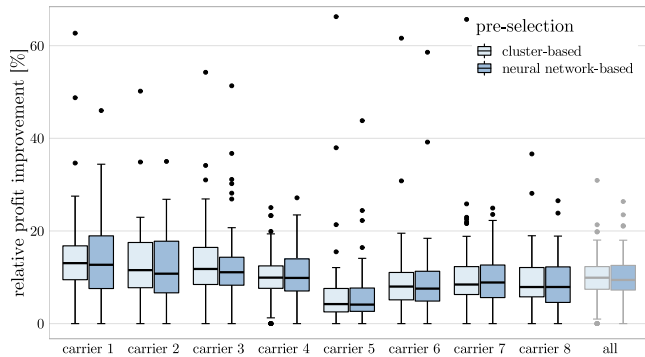
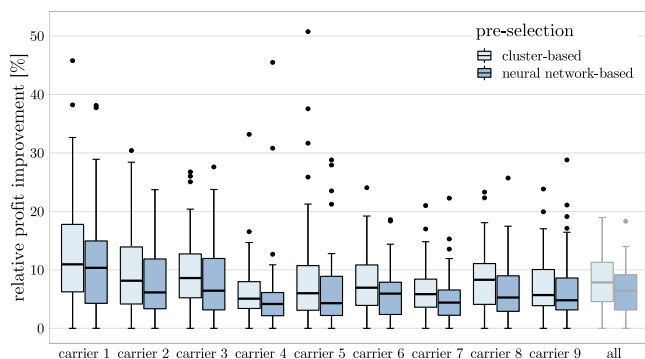
From the maximum and minimum RPIs in Table 1, it can be seen that there are rather simpler and harder instances, respectively, i. e., some instances have a bigger potential for optimization than others. On the one hand, this can result due to the initial acquisition of requests and on the other hand because of the data structure itself, i. e., the variety between the instances regarding size of the time windows or vehicle capacities (see Li and Lim, 2001). Though, there are some instances with bigger potential than the bundle selection approach exploited (see max. RPI), over all instances the gap between the average RPI for the collaborative approach and the centralized optimization is very small for both cooperation network structures.

In Table 2, further results on the auction process itself are presented. The table shows mean values over all 4-, 6-, 8- and 9-depot instances for the number of requests within the cooperation network  $\bar{n}_{\text{req}}$ , the auction pool size  $\bar{p}$ , the ratio of released requests regarding the total number of requests  $\frac{\bar{p}}{\bar{n}_{\text{req}}}$  as well as the relation of released to reserved requests  $\frac{\bar{p}}{\bar{n}_{\text{req}} - \bar{p}}$ . Additionally, the number of bundles pre-selected and finally selected (for the bidding process) are depicted for both pre-selection approaches CB and NN. It can be seen from the results that about 25% in the 4-depot, 29% in the 6-depot, 33% in the 8-depot

**Table 2**

Mean values over all 4-, 6-, 8- and 9-depot instances of number of requests  $\bar{n}_{\text{req}}$ , number of requests within the auction pool  $\bar{p}$ , ratio of number of auction pool and total requests within the cooperation network  $\frac{\bar{p}}{\bar{n}_{\text{req}}}$ , ratio of released to reserved requests  $\frac{\bar{p}}{\bar{n}_{\text{req}} - \bar{p}}$  and number of bundles pre-selected as well as finally selected for both approaches CB and NN.

	$\bar{n}_{\text{req}}$	$\bar{p}$	$\frac{\bar{p}}{\bar{n}_{\text{req}}}$	$\frac{\bar{p}}{\bar{n}_{\text{req}} - \bar{p}}$	Bundles pre-selected		Finally selected	
					CB	NN	CB	NN
4d	101.67	25.30	24.89%	33.82%	9,120.57	197.70	9.72	10.15
6d	173.27	49.65	28.66%	41.38%	11,294.28	315.20	14.82	15.22
8d	232.00	77.53	33.35%	51.21%	16,121.72	1,090.38	27.85	24.27
9d	240.93	67.75	28.16%	40.04%	14,335.28	846.52	31.12	28.93

**Fig. 11.** Boxplot of rel. profit improvement in 60 periods for 6-depot collaboration network.**Fig. 12.** Boxplot of rel. profit improvement in 60 periods for 8-depot collaboration network.**Fig. 13.** Boxplot of rel. profit improvement in 60 periods for 9-depot collaboration network.

and 28% in the 9-depot instances of the requests are released for exchange. Since the bundle creation by the auctioneer depends on the number of requests within the auction pool, this naturally results in more possible bundles and thus higher computational time for the 8-depot instances compared to the other data sets as it can be seen in Table 1. Therefore, the number of bundles generated in the pre-selection approaches is also larger for the 8-depot instances than the remaining data sets. Moreover, the number of pre-selected bundles in the neural network-based technique is remarkably smaller than in the cluster-based approach. This results in a much faster approach (cf. NN results in Table 1). The number of finally selected bundles which are given to the auction process can be reduced significantly through the scenario-based bundle reduction (cf. Section 5.1) while keeping efficiency with respect to the profit improvement. In both cases (CB and NN) the number of bundles and thus the number of bids to be determined is less than the number of requests within the auction pool. This implies that the carriers within this cooperation network have to calculate even less bids than if the requests are offered in a single item auction.

In what follows, we take a closer look at the pre-selection variants themselves. In Figs. 10, 11, 12 and 13, boxplots regarding the different types of collaboration networks are presented, in which the relative profit improvement is depicted over all instances. Please note that the outliers over a certain value (bigger than 60%) are not included in the boxplots. It is shown that the neural network-based pre-selection achieves similarly good results in terms of individual profit increase as the cluster-based approach, since the median's values are close to each other. Please note that the latter is a more stable method over almost every carrier for both collaboration network types due to the tighter box plots. A reason for this is that the  $k$ -means approach generates a higher variety within the generated bundles (e.g., bundle size). Consequently, this leads to a more complex auction process and thus to higher computational time (cf. Table 1). However, the cluster-based pre-selection technique can be applied on each collaboration network independently of the instance structure. For example, if the participating carriers of the collaboration network changes, the cluster-based pre-selection can be used immediately, while the neural network-based technique has to be trained again with new artificially created instances, which are similar to the new structure of the collaboration network. It is worth to mention that this pre-processing step can be done in short time due to the fact that we do not need very high accuracy of the neural network. If the accuracy is too high, the bundles created by the random choice based on the probability matrix coming from the neural network would have too low variety, and thus hinder the outcome of the request exchange through the auction.

The profit allocation within the cooperation network with 4 depots seems to be a bit fairer than within the network consisting of 6 depots. Fig. 11 displays that carriers 1 and 2 obtain a higher benefit from the cooperation. This is because these carriers are located in the middle of the collaboration network with respect to their customer region.<sup>1</sup> Thus, they have a higher potential to contribute to a bigger profit improvement within the cooperation than others located on the edges of the network's plane, e.g., during request releasing in step (i), that in turn is rewarded in the profit allocation. In order to maximize the incentive for staying within the cooperation, this effect has to be implemented in the profit allocation process (cf. step (v), Section 4). Consequently, carriers which cannot contribute in a suitable manner

<sup>1</sup> This effect can also be found in the 8-depot data set for carriers 1, 2, 3 and 4 (cf. Fig. 12) as well as in the 9-depot instances for carrier 1 (cf. Fig. 13).

naturally due to their location in the collaboration network ought not to be disadvantaged.

## 7. Conclusion

In this paper, we have presented a decentralized and double auction-based collaboration approach for request exchange in the less-than-truckload market, i.e., routing is modelled as pickup and delivery problem with time windows and heterogeneous vehicle fleets. For this purpose, we have adopted a request exchange procedure introduced by Berger and Bierwirth (2010) and extended this in order to apply it on the underlying routing problem. In particular, we have focused on the selection of bundles, since this step has the biggest impact on the outcome of the collaboration. The auctioneer carries out this selection in order to offer attractive bundles in the auction process maximizing the profit. Since this is a stochastic problem, a scenario-based bundle selection approach has been developed in combination of two pre-selection techniques, a cluster- and a neural network-based pre-selection. All pre-selected bundles are valued by an attractiveness value, in which several bundle attributes are included. In order to evaluate these selection variants, 4-, 6-, 8- and 9-depot cooperation network data sets were generated with 240 problem instances in total by using the well-known (Li and Lim, 2001) benchmark. The collaboration framework has been compared to the individual transportation planning (lower threshold) and the centralized planning (upper threshold) with respect to the profit improvement. It could be shown that the scenario-based bundle selection approach provided a relative profit increase of about 6.82% to 10.71% on average (depending on the considered cooperation network structure as well as the pre-selection technique) and up to 43.49% at its best compared to the individual planning. Moreover, the profit exhausts at least 53.5% of the centralized transportation planning potential on average. Therefore, the collaborative framework with scenario-based bundle selection is a reasonable approach for solving the collaborative PDPTWHV, while the neural network-based pre-selection technique is faster, but determines slightly worse profit improvement than the cluster-based technique. However, the cluster-based pre-selection is more stable and can be applied on each collaboration network structure immediately without any pre-processing steps.

In future research, an approach for parameter tuning that finds the optimal weights for the attributes within the attractiveness value can be applied. In this way, the estimation of bids will be further enhanced and thus the selection will lead to better bundles for the auction process. Since the neural network-based pre-selection appears promising, an extended research should be conducted to investigate how the structure of the feed-forward neural networks can be optimized to improve the assignment estimation. Particularly, also other (machine learning) classification techniques, such as self-organizing maps, might be conceivable in the pre-selection process and worth to investigate their impact. It is worth examining how the ratio of released requests impacts the profit increase of the cooperation network, thus appropriate releasing strategies used in step (i) are supposed to be developed and evaluated in combination to the proposed bundle selection approaches. Finally, as we have seen that the profit allocation method strongly depends on the structure of the cooperation network, i.e., where a participating carrier is located, this information has to be included into the profit distribution to achieve fairness.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Table 3**

Indices, sets, variables and parameters (alphabetically ordered)

Indices and sets:	
$B \in \mathcal{B}$	Set of offered bundles during the auction process; every bundle $B$ contains several requests, $B = \{B_1, \dots, B_p\} \subseteq 2^{\mathcal{P}}$
$B \in \mathcal{B}_\sigma$	Set of bundles for a certain scenario $\sigma$ within the stochastic BuSP
$c \in \mathcal{C}$	Set of carriers (or bidders in the auction problem), $\mathcal{C} = \{c_1, \dots, c_m\}$
$r \in \mathcal{P}$	Requests within the auction pool $\mathcal{P} = \{r_1, \dots, r_p\}$
$r \in \mathcal{R}$	Set of requests of all carriers, $\mathcal{R} = \{r_1, \dots, r_n\}$ , $n > p$
$r \in \mathcal{R}_c$	Set of requests acquired by carrier $c \in \mathcal{C}$
$r \in \mathcal{R}'_c$	Set of retained requests of carrier $c \in \mathcal{C}$ after releasing the offered ones to the auction pool $\mathcal{P}$
$\sigma \in \mathcal{S}$	Set of scenarios $\sigma$ within the stochastic BuSP
Parameters:	
$a_c$	Ask price that carrier $c \in \mathcal{C}$ needs at least to compensate the lost profit due to the offered requests for the auction process
$b_{c,B}$	Bid of carrier $c \in \mathcal{C}$ for bundle $B \in \mathcal{B}$ within the auction process
$c_B$	Centroid of a bundle $B \in \mathcal{B}$ respecting direct travel distances $t_r$ and the midpoints between pickup and delivery customers of all requests $r$ in bundle $B$
$\chi_{r,c}$	Binary allocation parameter that indicated if a request $r \in \mathcal{R}$ is acquired by carrier $c \in \mathcal{C}$ ( $\chi_{r,c} = 1$ ) or not ( $\chi_{r,c} = 0$ )
$\delta_B$	Density of bundle $B \in \mathcal{B}$ based on direct travel distances $t_r$ of all requests $r$ in bundle $B$ and the bundle's centroid $c_B$
$d_c$	Depot node of carrier $c \in \mathcal{C}$
$\eta_{c,B}$	Attractiveness measure of bundle $B \in \mathcal{B}$ for carrier $c \in \mathcal{C}$
$\kappa$	maximum number of bundles chosen in the BuSP (or by the scenario-based bundle selection approach)
$l_B$	Length of the vehicle routing solution serving all requests in bundle $B \in \mathcal{B}$ taking time windows into account
$n^a, \tilde{n}^a$	Number of times requests are assigned to certain cluster centres or carriers determined by $k$ -means in the cluster-based or by the DFNN in the neural network-based pre-selection, respectively
$n^c$	Number of times $k$ -means is applied in the cluster-based pre-selection technique
$p$	Number of requests included within the auction pool, i.e., $p =  \mathcal{P} $
$p_{c,B}$	The price that has to be paid by carrier $c \in \mathcal{C}$ for bundle $B \in \mathcal{B}$ if $c$ has won $B$ during the auction process
$\pi_{c,B}$	Profit allocation $\pi_{c,B}$ for carrier $c \in \mathcal{C}$ and bundle $B \in \mathcal{B}$
$\pi_c$	Total profit allocation $\pi_c$ for carrier $c$
$\rho_r$	Revenue for serving a request $r \in \mathcal{R}$
$t_r$	Direct travel distance of a request $r \in \mathcal{R}$ , i.e., the distance between pickup and delivery customer
$v_B$	Number of vehicles needed to serve all requests in bundle $B \in \mathcal{B}$ taking time windows into account
$v_{c,B}$	True valuation of carrier $c \in \mathcal{C}$ for bundle $B \in \mathcal{B}$
$v_c$	True valuation of carrier $c \in \mathcal{C}$ for all released requests $r \in \mathcal{R}_c \setminus \mathcal{R}'_c$
$\tilde{b}_{c,B}^{\text{bid}}$	Best bid approximation for bundle $B \in \mathcal{B}$ and carrier $c \in \mathcal{C}$ depending on attractiveness $\eta_{c,B}$
Decision variables and distributions:	
$\Xi_{c,B}$	Triangular distribution for modelling stochastic bids of bundle $B \in \mathcal{B}$ from carrier $c \in \mathcal{C}$ depending on the best bid approximation $\tilde{b}_{c,B}^{\text{bid}}$
$y_{c,B}$	Binary variable that indicates if bundle $B \in \mathcal{B}$ is allocated to carrier $c \in \mathcal{C}$ ( $y_{c,B} = 1$ ) or not ( $y_{c,B} = 0$ )

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## Appendix A

In the appendix, we give information about notations (cf. Table 3) and parameter (cf. Table 4) settings that are necessary for the collaborative framework.

**Table 4**  
Parameter settings of the collaboration framework.

Approach	Parameter	Value	Description
Grouping GA	$n^{\text{pop}}$	50	Population size
	$n^{\text{gen}}$	200	GA's number of generations while routing/bidding
	$p^{\text{cross}}$	1.0	Crossover probability
	$p^{\text{mut}}$	0.3	Mutation probability
Scenario-based bundle selection	$\alpha$	0.15	Weight for bundle's revenue
	$\beta$	1.65	Weight for number of requests within bundle
	$\gamma$	0.2	Weight for number of vehicles
	$\mu$	0	Weight for density
	$\nu$	0	Weight for bundle's tour length
	$\tau$	1.5	Weight for depot bundle distance
	$n^{\text{scenario}}$	50	Number of scenarios
Cluster-based pre-selection	$n^c$	40	Number of $k$ -means runs
	$n^a$	25	Number of request to cluster assignments in each run
Neural network pre-selection	$\tilde{n}^a$	30	Number of request to carrier assignments

## References

- Ackermann, H., Ewe, H., Kopfer, H., Küfer, K.-H., 2011. Combinatorial auctions in freight logistics. *Comput. Logist.* 6971, 1–17. [http://dx.doi.org/10.1007/978-3-642-24264-9\\_1](http://dx.doi.org/10.1007/978-3-642-24264-9_1).
- Aggarwal, C.C., 2018. *Neural Networks and Deep Learning*. Springer International Publishing, <http://dx.doi.org/10.1007/978-3-319-94463-0>.
- Berger, S., Bierwirth, C., 2010. Solutions to the request reassignment problem in collaborative carrier networks. *Transp. Res. E: Logist. Transp. Rev.* 46, 627–638. <http://dx.doi.org/10.1016/j.tre.2009.12.006>.
- Bichler, M., Schneider, S., Guler, K., Sayal, M., 2011. Compact bidding languages and supplier selection for markets with economies of scale and scope. *European J. Oper. Res.* <http://dx.doi.org/10.1016/j.ejor.2011.03.048>.
- BWOR, 2020. URL <https://www.uni-hildesheim.de/fb4/institute/bwl/betriebswirtschaft-und-operations-research/>. (Accessed 19 June 2022).
- Chen, H., 2016. Combinatorial clock-proxy exchange for carrier collaboration in less than truck load transportation. *Transp. Res. Part E: Logist. Transp. Rev.* 91, 152–172. <http://dx.doi.org/10.1016/j.tre.2016.04.008>.
- Clarke, E.H., 1971. Multipart pricing of public goods. *Public Choice* 11, 17–33. <http://dx.doi.org/10.1007/BF01726210>.
- Cleophas, C., Cottrill, C., Ehmeke, J.F., Tierney, K., 2019. Collaborative urban transportation: Recent advances in theory and practice. *European J. Oper. Res.* 273 (3), 801–816. <http://dx.doi.org/10.1016/j.ejor.2018.04.037>.
- Dahl, S., Derigs, U., 2011. Cooperative planning in express carrier networks – An empirical study on the effectiveness of a real-time decision support system. *Decis. Support Syst.* 51, 620–626. <http://dx.doi.org/10.1016/j.dss.2011.02.018>.
- Dai, B., Chen, H., 2011. A multi-agent and auction-based framework and approach for carrier collaboration. *Logist. Res.* 3, 101–120. <http://dx.doi.org/10.1007/s12159-011-0046-9>.
- Dai, B., Chen, H., Yang, G., 2014. Price-setting based combinatorial auction approach for carrier collaboration with pickup and delivery requests. *Int. J. Oper. Res.* 14, 361–386. <http://dx.doi.org/10.1007/s12351-014-0141-1>.
- de Vries, S., Vohra, R.V., 2003. Combinatorial auctions: A survey. *Inform. Comput.* 15, 284–309. <http://dx.doi.org/10.1287/ijoc.15.3.284.16077>.
- Eiben, A., Smith, J., 2015. *Introduction to Evolutionary Computing*, second Auflage ed. Springer, <http://dx.doi.org/10.1007/978-3-662-44874-8>.
- Gansterer, M., Hartl, R.F., 2016a. Combinatorial auctions in collaborative vehicle routing. *IFORS News* 10, 15–16.
- Gansterer, M., Hartl, R.F., 2016b. Request evaluation strategies for carriers in auction-based collaborations. *OR Spectrum* 38, 3–23. <http://dx.doi.org/10.1007/s00291-015-0411-1>.
- Gansterer, M., Hartl, R.F., 2018a. Centralized bundle generation in auction-based collaborative transportation. *OR Spectrum* 40, 613–635. <http://dx.doi.org/10.1007/s00291-018-0516-4>.
- Gansterer, M., Hartl, R.F., 2018b. Collaborative vehicle routing: A survey. *European J. Oper. Res.* 268, 1–12. <http://dx.doi.org/10.1016/j.ejor.2017.10.023>.
- Gansterer, M., Hartl, R.F., 2020. Shared resources in collaborative vehicle routing. *TOP* 28 (1), 1–20. <http://dx.doi.org/10.1007/s11750-020-00541-6>.
- Gansterer, M., Hartl, R.F., Savelsbergh, M., 2019a. The value of information in auction-based carrier collaborations. *Int. J. Prod. Econ.* 221, 107485. <http://dx.doi.org/10.1016/j.ijspe.2019.09.006>.
- Gansterer, M., Hartl, R.F., Sørensen, K., 2020. Pushing frontiers in auction-based transport collaborations. *Omega* 94, 102042. <http://dx.doi.org/10.1016/j.omega.2019.01.011>.
- Gansterer, M., Hartl, R.F., Vetschera, R., 2019b. The cost of incentive compatibility in auction-based mechanisms for carrier collaboration. *Networks* 73, 490–514. <http://dx.doi.org/10.1002/net.21828>.
- Groves, T., 1973. Incentives in teams. *Econometrica* 41, 617–631. <http://dx.doi.org/10.2307/1914085>.
- Jain, R., Varaiya, P., 2007. The combinatorial seller's bid double auction: An asymptotically efficient market mechanism. URL [www.gbcenter.org/archive/conf07/downloads/conf/Jain492.pdf](http://www.gbcenter.org/archive/conf07/downloads/conf/Jain492.pdf).
- Karaenke, P., Bichler, M., Minner, S., 2019. Coordination is hard: Electronic auction mechanisms for increased efficiency in transportation logistics. *Manage. Sci.* 65 (12), 5884–5900. <http://dx.doi.org/10.1287/mnsc.2018.3208>.
- Karels, V.C., Veelen, L.P., Van Woensel, T., 2020. An auction for collaborative vehicle routing: Models and algorithms. *EURO J. Transp. Logist.* 9 (2), 100009. <http://dx.doi.org/10.1016/j.ejtl.2020.100009>.
- Krajewska, M.A., Kopfer, H., 2006. Collaborating freight forwarding enterprises: Request allocation and profit sharing. *OR Spectrum* 28, 301–317. <http://dx.doi.org/10.1007/s00291-005-0031-2>.
- Krajewska, M.A., Kopfer, H., Laporte, G., Ropke, S., Zaccour, G., 2008. Horizontal cooperation among freight carriers: Request allocation and profit sharing. *J. Oper. Res. Soc.* 59, 1483–1491. <http://dx.doi.org/10.1057/palgrave.jors.2602489>.
- Krishna, V., 2010. *Auction Theory*, second ed. Academic Press, <http://dx.doi.org/10.1016/C2009-0-22474-3>.
- Li, H., Lim, A., 2001. A metaheuristic for the pickup and delivery problem with time windows. *Int. J. Artif. Intell. Tools* 12, 160–167. <http://dx.doi.org/10.1109/ICTAI.2001.974461>.
- Liu, P., Wu, Y., Xu, N., 2010. Allocating collaborative profit in less-than-truckload carrier alliance. *J. Serv. Sci. Manag.* 3, 143–149. <http://dx.doi.org/10.4236/jssm.2010.31018>.
- McAfee, R.P., McMillan, J., 1987. Auctions and bidding. *J. Econ. Lit.* 25, 699–738. <https://EconPapers.repec.org/RePEc:aea:jeclit:v:25:y:1987:i:2:p:699-738>.
- Myerson, R.B., Satterthwaite, M.A., 1983. Efficient mechanisms for bilateral trading. *J. Econom. Theory* 28, 265–281. [http://dx.doi.org/10.1016/0022-0531\(83\)90048-0](http://dx.doi.org/10.1016/0022-0531(83)90048-0).
- Narayanan, U., Unnikrishnan, A., Paul, V., Joseph, S., 2017. A survey on various supervised classification algorithms. In: 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing. ICECDS, pp. 2118–2124. <http://dx.doi.org/10.1109/ICECDS.2017.8389824>.
- Pankratz, G., 2005. A grouping genetic algorithm for the pickup and delivery problem with time windows. *OR Spectrum* 27, 21–41. <http://dx.doi.org/10.1007/s00291-004-0173-7>.
- Pekeč, A., Rothkopf, M.H., 2003. Combinatorial auction design. *Manage. Sci.* 49 (11), 1445–1615. <http://dx.doi.org/10.1287/mnsc.49.11.1485.20585>.
- Rahul, J., Varaiya, P., 2009. The combinatorial seller's bid double auction: An asymptotically efficient market mechanism.
- Rokach, L., 2009. A survey of clustering algorithms. In: Maimon, O., Rokach, L. (Eds.), *Data Mining and Knowledge Discovery Handbook*. Springer, Boston, MA, [http://dx.doi.org/10.1007/978-0-387-09823-4\\_14](http://dx.doi.org/10.1007/978-0-387-09823-4_14), chapter 14.
- Roman, I., Ceberio, J., Mendiburu, A., Lozano, J.A., 2016. Bayesian optimization for parameter tuning in evolutionary algorithms. In: 2016 IEEE Congress on Evolutionary Computation. CEC, pp. 4839–4845. <http://dx.doi.org/10.1109/CEC.2016.7744410>.
- Rüther, C., Rieck, J., 2020. A grouping genetic algorithm for multi depot pickup and delivery problems with time windows and heterogeneous vehicle fleets. In: Paquete, L., Zarges, C. (Eds.), *Evolutionary Computation in Combinatorial Optimization*. EvoCOP 2020, In: Lecture Notes in Computer Science, vol. 12102, Springer, Cham., pp. 148–163. [http://dx.doi.org/10.1007/978-3-030-43680-3\\_10](http://dx.doi.org/10.1007/978-3-030-43680-3_10).
- Schiller, T., Maier, M., Büchle, M., 2017. *Global truck study 2016*. Deloitte.
- Schopka, K., 2018. *Tourenplanung kooperierender Spediteure unter Aspekten des dynamischen Teilladungsverkehrs* (Ph.D. thesis). Universität Bremen, URL <https://d-nb.info/1155300637/34>.



- Schopka, K., Kopfer, H., 2017. Pre-selection strategies for collaborative vehicle routing problem with time windows. In: Freitag, M., Kotzab, H., Pannek, J. (Eds.), Dynamics in Logistics. In: Lecture Notes in Logistics, Springer, Cham, pp. 231–242. [http://dx.doi.org/10.1007/978-3-319-45117-6\\_21](http://dx.doi.org/10.1007/978-3-319-45117-6_21).
- Shapiro, A., Dentcheva, D., Ruszczyński, A., 2009. Lectures on Stochastic Programming: Modeling and Theory. Society for Industrial and Applied Mathematics (SIAM) and Mathematical Programming Society (MPS), <http://dx.doi.org/10.1137/1.9780898718751>.
- SINTEF, 2008. URL <https://www.sintef.no/projectweb/top/pdptw/li-lim-benchmark/>. (Accessed 19 June 2022).
- Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R., 2014. Dropout: A simple way to prevent neural networks from overfitting. J. Mach. Learn. Res. 15, 1929–1958, <https://dl.acm.org/doi/10.5555/2627435.2670313>.
- Statista, 2017. Führende logistikdienstleister im bereich stückgut nach umsatz in deutschland im jahr 2015. Deutsche Verkehrszeitung 82, 9.
- Verdonck, L., Beullens, P., Caris, A., Ramaekers, K., Janssens, G.K., 2016. Analysis of collaborative savings and cost allocation techniques for the cooperative carrier facility location problem. J. Oper. Res. Soc. 67, 853–871. <http://dx.doi.org/10.1057/jors.2015.106>.
- Vickrey, W., 1961. Counterspeculation, auctions, and competitive sealed tenders. J. Finance 16, 8–37. <http://dx.doi.org/10.1111/j.1540-6261.1961.tb02789.x>.
- Wang, X., Kopfer, H., 2014. Collaborative transportation planning of less-than-truckload freight: A route-based request exchange mechanism. OR Spectrum 36 (2), 357–380. <http://dx.doi.org/10.1007/s00291-013-0331-x>.
- Wang, X., Kopfer, H., Gendreau, M., 2014. Operational transportation planning of freight forwarding companies in horizontal coalitions. European J. Oper. Res. 237 (3), 1133–1141. <http://dx.doi.org/10.1016/j.ejor.2014.02.056>.
- Wang, Y., Yuan, Y., Guan, X., Wang, H., Liu, Y., Xu, M., 2019. Collaborative mechanism for pickup and delivery problems with heterogeneous vehicles under time windows. Sustainability 11, 3492. <http://dx.doi.org/10.3390/su11123492>.
- Zhang, G.P., 2000. Neural networks for classification: A survey. IEEE Trans. Syst., Man, Cybern., Part C (Applications and Reviews) 30, 451–462. <http://dx.doi.org/10.1109/5326.897072>.