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The collaborative consistent vehicle routing problem with workload balance

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ABSTRACT

The rising competition in the logistics sector forces companies to be more economically efficient. One of the major sources of inefficiency is the incomplete usage of available resources, such as vehicles' capacities. Mechanism that allow to better exploit such resources by enabling carrier collaborations are on the rise. Our study examines a centrally organized multi-period collaborative vehicle routing problem, where carriers can exchange customers who have to be serviced on a regular basis. Collaborations, where carriers serve frequent customers, are supposed to face the problem of (i) time consistency in terms of visiting time, and of (ii) service consistency. The latter ensures that customers are visited by the same collaboration partner throughout the whole planning horizon. Additionally, carriers might only be willing to enter a collaboration if a minimum market share can be guaranteed. In order to take all these issues into account, we introduce the collaborative vehicle routing problem with time and service consistency and workload balance. The mathematical model including several valid inequalities is presented. In a computational study, we solve small-sized instances to optimality. In order to tackle larger instances, we propose an efficient and effective matheuristic and an iterated local search algorithm. We show that both methods reach near optimal solutions within very short computational times. Managerial insights on the cost of imposing time and service consistency as well as workload balancing constraints are presented and discussed. We show that, according to our computational study, consistency constraints can be imposed for almost no additional cost, while workload balancing constraints do not have any negative effect on the total collaboration profit. This is a meaningful insight and might be a strong argument for carriers to enter collaborations.

1. Introduction

The transportation industry has become a very competitive environment. While the number of market players has grown considerably, customers are becoming more and more demanding. Therefore, companies need to provide efficient transportation services at low prices in order to stay in business. Consequently, profit margins have considerably declined.

To increase their efficiency, carriers can establish collaborations in which they share their fleets with the aim to maximize their profit and reduce operational costs.

Collaborations may be centralized, where decisions are made by an external decision maker having complete information (Gansterer & Hartl, 2018b). In decentralized collaborations no such fully informed decision maker exists. Obviously, centralized collaborations allow a better exploitation of the available resources. This yields advantages not only for the transportation companies, but also for other stakeholders, like residents or public authorities. This is particularly true, if environmental objectives are taken into account. However, while for ecological goals the objective is to minimize emissions, road congestion and noise pollution, the goal for each individual carrier is to maximize the carrier's own profit. For this reason, carriers are interested to taking part in collaborations

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only if this allows them to increase their individual profit compared to operating individually.

Several studies on collaborations in vehicle routing problems (VRP) have been presented in the literature (Gansterer & Hartl, 2018b), but none of them addresses periodic or multi-period problems. Collaborations where carriers serve customers that need to be visited on a regular basis face the problem of consistency in terms of (i) visiting time, and of (ii) service (Groer, Golden, & Wasil, 2009). The latter ensures that customers are visited by the same collaboration partner throughout the whole planning horizon. This is a practically relevant assumptions, since it is assumed that service consistency increases customer satisfaction and improves loyalty and operations efficiency.

Another issue related to consistency is the fact that each customer must always be visited by the same driver. However, this second requirement may become too restrictive in practical applications (Kovacs, Golden, Hartl, & Parragh, 2015). Therefore, consistency of service can be ensured by allowing customers to be visited by a restricted number of drivers. In a collaborative environment, a similar concept can be introduced, which is to impose that customers have to be served by the same carrier (but by different drivers).

Collaborative transportation systems often suffer from *winner-takes-all* effects (Gansterer, Hartl, & Wieser, 2020a), which lead to solutions where a small share of carriers serve the great majority of customers. To avoid these unbalanced workloads, a minimum number of customers served by each carrier should be ensured.

The goal of this work is to analyze the impact of consistency and workload balance in centralized collaborative transportation systems. The objective is to (i) maximize total collaboration profit, to (ii) ensure an increment of profit for all participants in the coalition, with respect to the profit they would have reached without entering the collaboration, and to (iii) provide high-level customers service, ensuring both time and service consistency.

The contribution of our work is fourfold:

1. We are the first to introduce the collaborative VRP with time and service consistency and workload balance (CCVRP).
2. The problem is formulated mathematically and strengthened by several valid inequalities.
3. We design an efficient and effective matheuristic (MH) and compare it to an Iterated Local Search (ILS) algorithm, which is able to solve larger instances.
4. We provide managerial insights, where the most surprising one is that workload balancing can be imposed for no additional cost, while consistency of time and of service can be achieved by only a marginal decrease in the total collaboration profit. A surprising finding is that minimum per period profits are extremely expensive and do not allow for successful collaborations.

The rest of the paper is organized as follows. Related literature is discussed in Section 2. We define and formulate the newly introduced problem in Section 3. The proposed solution approaches are described in Section 4. We present numerical experiments and identify managerial insights in Section 5 and summarize our work in Section 6.

2. Literature review

The VRP was introduced by Dantzig and Ramser (1959). To this day, it remains one of the most widely studied problems in the field of combinatorial optimization (Kritikos & Ioannou, 2010). Given a fleet of vehicles and a set of transportation requests, the task is to determine the optimal set of routes to fulfill these requests while satisfying specific constraints (Irnich, Toth, & Vigo, 2014). In our literature review, we include studies focusing on the following related extensions of the classical VRP: periodic VRPs, consistency, fairness aspects, and collaborative vehicle routing.

Problems, where a routing plan has to be provided for several days, in which customers have to be visited regularly, are referred to *periodic* VRP (PVRP). Such problems are commonly faced in grocery distribution and waste collection (Hemmelmayr, Dörner, & Hartl, 2009). This topic has been broadly addressed in the literature starting from the seminal paper of Beltrami and Bodin (1974) and many solution approaches have been proposed, among which, the very recent paper by Chen, Shen, and Hong (2019).

The consistent VRP aims for routes that are minimal in cost but at the same time fulfill a certain level of customer satisfaction. The latter is indicated by customers' requirements on consistency. Routes can be consistent in visting time or in the driver who serves a customer (Groer et al., 2009). The state-of-the-art exact and heuristics algorithms to address the consistent VRP are those proposed in Goeke, Roberti, and Schneider (2019). In the generalized consistent VRP, each customer is visited by a limited number of drivers and the variation in the arrival times is penalized in the objective function (Kovacs et al., 2015). A literature survey is presented by Kovacs, Golden, Hartl, and Parragh (2014a). A template-based metaheuristic for the consistent VRP is proposed by Kovacs, Parragh, and Hartl (2014b) and Tarantilis, Stavropoulou, and Repoussis (2012). Campelo, Neves-Moreira, Amorim, and Almada-Lobo (2019) tackle VRP with consistency and service level agreements in the pharmaceutical industry. A multi-period dial-a-ride problem with driver consistency is presented in Braekers and Kovacs (2016). Exact approaches for the periodic VRP with driver consistency are presented by Rodríguez-Martín, Salazar-González, and Yaman (2019).

In recent years equity and fairness aspects have been gaining recognition in both real-world applications and theoretical studies in the field of vehicle routing. Balanced resource utilization and a fair workload distribution have been found to provide non-monetary benefits, such as employee satisfaction, increased customer service, and flexible resource availability (Matl, Hartl, & Vidal, 2019). As a result, these aspects have been included in vehicle routing models (Bektaş, 2013; Huang, Smilowitz, & Balcik, 2012; Jozefowiez, Semet, & Talbi, 2009; Kritikos & Ioannou, 2010), and (Jozefowiez, Semet, & Talbi, 2008), either as a contribution in the objective function or by means of additional workload balance constraints. There is not a unique definition of *workload*. It can be defined as the number of customers visited by the driver, the amount of delivered load, or the tour length. Furthermore, it can be referred to a single planning period (e.g. a day) or to the whole planning horizon in case of periodic VRPs. In horizontal collaborations, i.e. when collaborating partners operate on the same level of the supply chain and could, therefore, become competitors, the inclusion of workload balancing constraints allows to have a fairer distribution of the workload among partners. This helps to overcome barriers and concerns that hinders companies to enter collaborations.(Buijs, van Wezel, & van Dooren, 2018; Cruijssen, Cools, & Dullaert, 2007b).

Potential benefits of collaborations in routing problems were initially examined in Krajewska and Kopfer (2006) and Cruijssen, Dullaert, and Fleuren (2007c). Several empirical studies have been conducted (Cruijssen et al., 2007b; Lydeka & Adomavičius, 2007 and Paterman, Cahoon, & Chen, 2016.), investigating issues and obstacles faced by companies when entering logistics partnerships. Sever real-world cases have been examined to assess potential collaboration gains. According to studies conducted by Cruijssen, Bräysy, Dullaert, Fleuren, and Salomon (2007a); Ergun, Kuyzu, and Savelsbergh (2007); Muñoz-Villamizar, Montoya-Torres, and Vega-Mejía (2015) and Chinh, Kim, Siwei, and NengSheng (2016), centralized planning may provide up to 20–30% profits improvement (Gansterer & Hartl, 2018b). Fernández, Roca-Riu, and Speranza (2018) study the collaborative gain in the case of shared customer VRP, i.e. in routing problems in which customers may require service by two or more partners in the coalition. They observe cost savings between 6% and 25%, depending on customers' geographical distribution. Gansterer, Hartl, and Salzmann (2018a) extend the collaborative pickup and delivery problem introduced by Berger and Bierwirth (2010) by including workload constraints for the single vehicle and single period problem and provide several exact solution approaches. The same problem is heuristically addressed and further analyzed in Gansterer et al. (2020a). The authors show that assignment constraints have a detrimental effect on collaboration gains in the case of single vehicle, while, when dealing with multiple vehicles, assignment constraints can be imposed at relatively low cost. The challenge of a fair cost or profit allocation in logistics collaboration is addressed by Hezarkhani, Slikker, and Van Woensel (2016); Liu, Wu, and Xu (2010) and Vanovermeire, Sörensen, Breedam, Vannieuwenhuyse, and Verstrepen (2014), among others.

Gansterer et al. (2018a) extend the collaborative pickup and delivery problem introduced by Berger and Bierwirth (2010) by including workload constraints for the single vehicle and single period problem. Several exact solution approaches are applied. The same problem is solved heuristically and further analyzed in Gansterer et al. (2020a). It is shown that assignment constraints for single vehicle collaborations, have a detrimental effect on collaboration gains, while for the single period problem with multiple vehicles, assignment constraints can be imposed at relatively low cost. The challenge of a fair cost or profit allocation in logistics collaboration is addressed by Hezarkhani et al. (2016); Liu et al. (2010) and Vanovermeire et al. (2014), among others.

Studies on decentralized collaborations, where no central decision maker exists, are presented by Krajewska and Kopfer (2006), Berger and Bierwirth (2010), Oezener, Ergun, and Savelsbergh (2011), Dai and Chen (2011), Xu, Huang, and Cheng (2016), and Gansterer and Hartl (2018a). Gansterer, Hartl, and Vetschera (2018b) elaborate on desirable game theoretical properties in auction-based transport collaborations.

Environmental aspects are considered by Ballot and Fontane (2010); Muñoz-Villamizar et al. (2015); Pérez-Bernabeu, Juan, Faulin, and Barrios (2015), and Schulte, Lalla-Ruiz, González-Ramírez, and Voß (2017). In addition to cost savings of 25%, Muñoz-Villamizar et al. (2015) observe a 9% reduction in the number of routes and a 10% increase in vehicle utilization factors which can in turn reduce emissions and congestion. Ballot and Fontane (2010) found a 25% reduction of gas emissions while studying collaborations in French retail chains.

Chabot, Bouchard, Legault-Michaud, Renaud, and Coelho (2018) investigate collaborations between shippers willing to synchronize their shipping operations. They present real data from three Canadian manufacturing companies, who, establishing a collaboration, have earned consistent reductions of both shipping and environmental costs.

Due to the problem-inherent complexity, collaborative VRP are often solved with local search-based metaheuristics (Defryn, Sörensen, & Cornelissens, 2016; Pérez-Bernabeu et al., 2015; Sanchez, Pradenas, Deschamps, & Parada, 2016). For decentralized settings, Berger and Bierwirth (2010), Gansterer, Küçüktepe, and Hartl (2017), and Gansterer, Hartl, and Sörensen (2019) propose auction-based systems.

We refer interested readers to Gansterer and Hartl (2018b) and Gansterer and Hartl (2020b) for a general overview of collaborative vehicle routing problems, to Cleophas, Cottrill, Ehmke, and Tierney (2018) for a focus on urban transportation, and to Guajardo and Rönnqvist (2016) for cost allocation mechanisms.

However, none of these studies consider the multi-vehicle *and* multi-period case. The aim of our study is to close this research gap.

3. The collaborative consistent vehicle routing problem with workload balance

In this problem, a set of carriers, K, has to serve a set of customers I, over a planning horizon composed of P periods. Each carrier k holds a subset of the total customers, A_k, but carriers can collaborate and share customers among each other if this leads to an increment of profit for each single carrier in the coalition. Each customer i requires to be visited in a given subset of the periods in P or possibly in all of them. For each visit to a customer i the service time, s_i^p, required to complete it, and the quantity to be delivered, q_i^p are known. To collect the revenue from a customer, π_i, it is necessary to perform all the requested visits. Carriers may freely exchange customers among each other but, for consistency purposes, all the tasks related to the same customer must be performed by the same carrier. Each carrier owns a fleet located in a given depot D_k, composed of V_k identical vehicles of capacity $Q^k_{\max}$. Each vehicle can perform a single route per period with a maximum duration $T_{\max}$ and a maximum cumulative load of $Q^k_{\max}$. Let us define the maximum capacity of a vehicle across all the carriers as $Q_{\max} = \max_k Q^k_{\max}$. The set of nodes involved in the network, N, is composed of $\cup_{k\in K} D_k \cup I$. Travel cost and time between each pair of nodes, i and j, are denoted as c_{ij} and t_{ij}, respectively. To avoid the *winner-takes-all* effect, the number of customers assigned to a carrier k cannot be lower than the number of customers originally served by k, $|A_k|$, reduced by a maximum allowed quantity α_k. For time consistency purposes the difference between the arrival time at customer i in two periods, in which a visit is scheduled, must differ by at most δ time units. In addition, the profit of each carrier must not be lower than the profit obtainable by the same carrier if it does not participate in the coalition, R_k. Service consistency is guaranteed by the fact that a customer can only be assigned to a specific carrier. The goal of the problem is to maximize the total profit of the carriers, given by the difference between the total revenue and the total travel costs.

3.1. Mathematical formulation

We provide the mathematical formulation of the CCVRP.
Let us define the following sets:

K	set of carriers
I	set of customers
A_k	set of customers of carrier k
P	set of periods
D	set of depots (D_k represents depot associated to carrier k)
N	set of nodes involved in the network $I \cup D$

Y_{ik}	binary variable taking value 1 if customer i is assigned to carrier k and 0 otherwise
X_{ij}^{kp}	binary variable taking value 1 if node j is visited immediately after node i by carrier k in period p and 0 otherwise
T_i^p	non-negative variable representing visit time of customer i on period p
L_i^p	non-negative variable representing cumulative load at node i in period p
$V_{kp}^{\min}$	integer variable representing the minimum number of vehicles needed to fulfill the demand assigned to carrier k in period p

$$\max \sum_{i\in I} \pi_i - \sum_{k\in K} \sum_{p\in P} \sum_{i\in N} \sum_{j\in N} c_{ij} X_{ij}^{kp} \tag{1}$$

$$\sum_{k \in K} Y_{ik} = 1 \qquad \forall i \in I \tag{2}$$

$$\sum_{i \in N} X_{ij}^{kp} \le Y_{jk} \qquad \forall j \in I, k \in K, p \in P \tag{3}$$

$$\sum_{i \in N} X_{ij}^{kp} = \sum_{i \in N} X_{ji}^{kp} \qquad \forall j \in I, k \in K, p \in P \tag{4}$$

$$\sum_{j \in I} X_{jD_k}^{kp} \le V_k \qquad \forall k \in K, p \in P \tag{5}$$

$$T_j^p \ge T_i^p + t_{ij} + s_i^p - T_{max}(1 - \sum_{k \in K} X_{ij}^{kp}) \qquad \forall j \in I, i \in N, p \in P \tag{6}$$

$$T_j^p + t_{ji} \sum_{k \in K} X_{ji}^{kp} \le T_{max} \qquad \forall j \in I, i \in \cup_{k \in K} D_k, p \in P \tag{7}$$

$$L_j^p \ge L_i^p + q_j^p - Q_{max}(1 - \sum_{k \in K} X_{ij}^{kp}) \qquad \forall j \in I, i \in N, p \in P \tag{8}$$

$$L_j^p \le Q_{max} \qquad \forall j \in I \tag{9}$$

$$X_{ij}^{kp} = 0 \qquad \forall j \in I \ \forall i \in D : i \neq D_k \ , p \in P, k \in K \tag{10}$$

$$X_{ji}^{kp} = 0 \qquad \forall j \in I, i \in D : i \neq D_k, p \in P, k \in K \tag{11}$$

$$\sum_{i \in N} \sum_{k \in K} X_{ij}^{kp} \ge q_j^p \frac{1}{Q_{max}} \qquad \forall j \in I, p \in P \tag{12}$$

$$T_i^p = 0 \qquad \forall i \in D, p \in P \tag{13}$$

$$L_i^p = 0 \qquad \forall i \in D, p \in P \tag{14}$$

$$|T_j^{p'} - T_j^{p''}| \le \delta \qquad \forall j \in I \ \forall p', p'' \in P : q_j^{p'} > 0 \ \ and \ \ q_j^{p''} > 0 \tag{15}$$

$$\sum_{j \in I} \pi_j Y_{jk} - \sum_{p \in P} \sum_{i \in N} \sum_{j \in I} c_{ij} X_{ij}^{kp} \ge R_k \qquad \forall k \in K \tag{16}$$

$$\sum_{j \in I} Y_{jk} \ge |A_k| - \alpha_k \qquad \forall k \in K \tag{17}$$

The objective function maximizes the total profit, which is the sum of collected revenues reduced by total travel costs (1). Constraints (2) impose that each customer is assigned to one and only one carrier. Constraints (3) ensure that a customer can be visited by a carrier only if it has been assigned to it. Constraints (4) are classical flow balance constraints, while constraints (5) fix the maximum number of vehicles a carrier can use. Arrival time at a customer is tracked through constraints (6) and route duration cannot exceed a maximum allowed value, $T_{\max}$, as imposed in (7). Similarly, cumulative load at a customer is tracked through constraints (8) while constraints (9) ensure that the maximum loading capacity of the vehicles, $Q^k_{\max}$, is respected. Only vehicles owned by a carrier can exit or enter the depot of that carrier. This is ensured in Constraints (10) and (11). If a customer requires some good in a given period it must be served in that period. This is formulated in constraints (12). Constraints (13) and (14) are operational constraints, which fix the earliest starting time from the depot and the cumulative load at the depot to 0, respectively. Arrival times consistency over periods is ensured by constraints (15). Each carrier's profit (i.e. revenue minus travel costs) must be equal or higher than the profit obtainable without taking part in the coalition. We ensure this by constraint (16). Finally, we use constraints (17) to maintain workload balance: the number of customers assigned to a given carrier cannot be lower than a minimum value imposed by the carrier. It is worth noting that R_k is computed solving the non collaborative version of the problem in which each carrier serves its customers. This problem can be decomposed into $|K|$ separate VRPs with consistency (one for each carrier).

Note that constraints (15) are not linear but can be linearized substituting them with constraints (18) and (19).

$$T_j^{p'} - T_j^{p''} \le \delta \qquad \forall j \in I \ \forall p', p'' \in P : q_j^{p'} > 0 \ \ and \ \ q_j^{p''} > 0 \tag{18}$$

$$T_j^{p''} - T_j^{p'} \le \delta \qquad \forall j \in I \ \forall p', p'' \in P : q_j^{p'} > 0 \ \ and \ \ q_j^{p''} > 0 \tag{19}$$

3.2. Valid inequalities

The minimum number of vehicles required to fulfill the demand of a carrier k in period p, $V_{kp}^{\min}$, can be bounded as follows.

$$V_{kp}^{min} \ge \sum_{i \in I} \frac{q_i^p Y_{ik}}{Q_{max}^k} \quad \forall k \in K, p \in P \tag{20}$$

Moreover, constraints (20) connect $V_{kp}^{\min}$ variables with Y_{ik} variables.

In order to strengthen the mathematical formulation we propose the following valid inequalities.

$$\sum_{i \in I} \pi_i Y_{ik} \ge R_k \qquad \forall k \in K \tag{21}$$

$$\sum_{i \in I} q_i^p Y_{ik} \le V_k Q_{max}^k \qquad \forall k \in K \ \ \forall p \in P \tag{22}$$

$$\sum_{i \in I} Y_{ik} \le min(|I|, |A_k| + \sum_{k' \in K: k' \neq k} \alpha'_k) \qquad \forall k \in K \tag{23}$$

$$\sum_{i \in I: q_i^p > 0} Y_{ik} + V_{kp}^{min} \le \sum_{i \in I \cup D} \sum_{j \in I \cup D} X_{ij}^{kp} \le \sum_{i \in I | q_i^p > 0} Y_{ik} + V_k \qquad \forall k \in K \ \ \forall p \in P \tag{24}$$

Constraints (21) imply that the sum of the revenues associated with the customers assigned to a specific carrier k must be greater than the best profit obtainable by this carrier without collaboration, R_k. This is based on the fact that the sum of collected revenues will be reduced by travel costs. Thus, the sum of the revenues is an upper bound for the actual profit of a carrier. If this upper bound is lower than R_k, the actual profit will be lower than R_k, and therefore, a solution where this set of customers is assigned to the carrier is infeasible. This does not depend on the assignment of customers to the other carriers. These valid inequalities are effective in limiting the solution space and in introducing an infeasibility check uniquely related to the customers assignment variables. Constraints (22) also operate directly on customers' assignment variables. They prevent assignments to a given carrier, where the total demand for a period exceeds the maximum demand manageable by the carrier in a single period. Constraints (23) produce an upper bound on the maximum number of customers that can be assigned to a given carrier. While constraints (21), (22), and (23) deal only with Y_{ik} variables, constraints (24) involve both Y_{ik} and X_{ij}^{kp} variables. These constraints provide tight lower and upper bounds on the number of X_{ij}^{kp} variables being simultaneously active (i.e., having a value of 1) for each carrier k and each period p, based on the number of customers that have been assigned to k and that have to be served in period p. The general idea of bounding the maximum number of arcs variables that can be simultaneously active, has been presented in Benavent, Corberan, Plana, and Sanchis (2011), where the authors exploit input data (such as maximum route length) to derive these bounds.

Instead, we use the customers-to-carriers assignment variables to provide much tighter bounds. This is based on the fact that not all customers require service in all periods.

4. Solution approaches

We use the Mixed Integer Programming (MIP) model presented in Section 3.1, for handling only small-sized instances with up to 20 customers, 4 carriers and 4 periods, as reported in Section 5. To handle larger instances, we propose a MH and an ILS approach. For ILS, MH is used as a blackbox local search tool. Generally, MH approaches have become very popular in the last decade. They cover different types of methods sharing the same main philosophy, the hybridization of mathematical programming and metaheuristics (Archetti & Speranza, 2014; Fischetti & Fischetti, 2016). Within this large family we identify two main groups. The first is composed of different (sequential) phases. In general, a metaheuristic is used to exploit the solution space, while, subsequently, a mathematical model is used to refine the obtained solution. This kind of matheuristic has been broadly applied to VRPs. A common procedure is to generate promising solutions with a randomized heuristic and to pass all obtained routes to a set partitioning formulation which selects the best combination of them (Mancini, 2017a; Montoya, Gueret, Mendoza, & Villegas, 2016). Another framework has been presented for the Electric VRP with Time Windows (EVRPTW), in which a metaheuristic is used to build up the routing plan, while a mathematical model is used to insert the visits to recharging stations along the route (Keskin & Catay, 2018; Montoya, Gueret, Mendoza, & Villegas, 2017).

The second group of matheuristics presents approaches where the mathematical model is used to efficiently explore the search neighborhood. In this group, very large neighborhoods can be exhaustively explored in relatively short computational times. Large neighborhood search-based matheuristics have been successfully applied to several routing problems (Mancini, 2016; 2017b; Mancini & Stecca, 2018). The matheuristics proposed in this paper belongs to this category of solution approaches.

4.1. Solution approach: MH

To solve the CCVRP, we propose a MH, where the MIP is used to explore very large neighborhoods. We do this by fixing a part of the solution and re-optimizing the remaining subproblem. Our method starts from an initial feasible solution. This solution can be obtained in different ways, by means of heuristic or truncated exact methods. We propose to run the MIP with a short time limit, TL_{init}, and to keep the best solution found. In case the MIP is not able to find a feasible solution within the time limit, the solution obtained when each carrier serves only its customers is kept as initial solution.

Then, for all the possible pairs of carriers, (k_1, k_2), we apply a local search mechanism, in which we fix the customers-to-carriers assignments (and consequently the routing plan) for all the remaining carriers, while re-optimizing the subproblem for k_1 and k_2. In this subproblem, available customers are assigned either to k_1 or to k_2. Consequently, routes for carriers, which are subject to consistency and workload constraints, have to be generated.

The MIP is run for the subproblem with a short time limit, TL. If the best solution obtained is better than the current best, we keep it as the current best, and start again exploring the entire set of carrier pairs. Otherwise, we proceed with the exploration of the pairs, which have not been selected so far. This procedure terminates when all pairs of carriers have been explored without finding any further improvement.

The pseudocode of MH is reported in Algorithm 1.

Algorithm 1 MH pseudocode.

```
compute an initial solution running MIP with TL_init and keep the best solution obtained so far
for all pairs of carriers (k1, k2) belonging to the list of carriers combinations do
    fix the routing of all the other carriers
    run the model, with a time limit TL only for k1 and k2 and customers currently assigned to them
    if the best solution obtained so far is better than the current solution then
        keep this solution as current best and restart exploring the list of carrier combinations
    end if
end for
```

We have developed a slightly different version of MH, named $MH^{\star}$ in which, differently from *MH*, we do not exhaustively explore the whole set of possible carrier pairs, but at each micro-iteration, we randomly draw two carriers to be jointly re-optimized. The algorithm stops after N_{noimp} unsuccessful micro-iterations. This version is particularly useful when the number of carriers is large and, consequently, the number of pairs to be explored is very large. On the contrary, when the number pairs is limited it is much more effective to explore all of them exhaustively. A detailed pseudocode of $MH^{\star}$ is reported in Algorithm 2.

Algorithm 2 $MH^{\star}$ pseudocode.

```
compute an initial solution running the model with TL_init and keep the best solution obtained so far
set noimp=0
while noimp < N_noimp do
    randomly select two carriers k1 and k2
    fix the routing of all the other carriers
    run the MIP, with a time limit TL, only for k1 and k2 and customers currently assigned to them
    if the best solution obtained so far is better than the current solution then
        keep this solution as current best and
        set noimp = 0
    else
        set noimp = noimp + 1
    end if
end while
```

4.2. Solution approach: ILS

In order to escape from local minima, we designed an approach based on ILS. For this, we use $MH^{\star}$, as the local search operator.

At each iteration of the ILS we run $MH^{\star}$. Once we find a local minimum, we perform a perturbation in the customer to carrier assignment and restart $MH^{\star}$ again.

If the solution obtained after the perturbation is infeasible, we discard it and perform another perturbation. The procedure terminates after a given number of restarts, N_{iter}.

The goal of the perturbation is to move toward a different area of the solution space in order to escape the current local minimum. This phase plays a crucial role, because, if we blindly move too far in the solution space (i.e., we change too many customer assignments), we risk restarting from a poor solution and consequently face a long computational time to move towards good quality solutions. On the other hand, if the perturbation is too small, we risk remaining trapped in the same local minimum. In the perturbation process, we randomly draw N_{pert} customers and assign them to a different carrier than in the current best solution. We stop the MIP after a short time limit TL_{pert} and keep the best solution obtained so far.

The pseudocode of the ILS procedure is reported in Algorithm 3.

Algorithm 3 ILS pseudocode.

```
run MH*
set iter=1
while iter < N_iter do
    apply a perturbation randomly selecting N_pert customers
    run the MIP with time limit TL_pert imposing that all the customers involved in the perturbation must be assigned to a different carrier than in the current best solution
    keep the best solution obtained so far as initial solution and run MH*
    if the best solution obtained is better than the current best then
        keep it as current best
    end if
    set iter = iter+1
end while
```

5. Computational study

Computational tests have been carried out on (i) 10 small-size instances with 20 customers (with a total of 49 visits), 4 periods and 4 carriers, and on (ii) 10 large-size instances with 50 customers (with a total of 150 visits), 5 periods and 8 carriers. For each customer i, the demand requested q_i^p and the service time s_i^p are the same for each period in which they require to be served. For both sets of instances, the value of V_k and α_k are set to 2. Tests have been executed on a system equipped with an Intel-i7-5500U processor running at 2.4 GHz clock speed and with 16 GB of RAM. All the procedures were developed in the Xpress-mosel language. The involved MIPs have been solved using the commercial solver Xpress 7.9.

The instances were derived from those used by Vidal, Crainic, Gendreau, Lahrichi, and Rei (2012) for the multi-depot periodic VRP, since, to the best of our knowledge, available instances for the consistent VRP have only one depot. Each carrier has been assigned to one of the depots and each customer has been randomly assigned to a carrier. Such instances allow to investigate a setting with a high level of competition among carriers, since customer regions are strongly overlapping. It has been shown by Berger and Bierwirth (2010) and Gansterer and Hartl (2018a) that these settings are the most promising ones as they yield the highest total collaboration profits. All instances are publicly available at Mancini, Gansterer, and Hartl (2020). The optimal value of R_k has been computed solving a simplified version of the mathematical model, where only one carrier and its initial customers are considered and constraints (16) and (17) are omitted. These values are reported at the end of each instance file in order to make experiments fully reproducible.

We set the maximum allowed difference in arrival time (δ) to 1 h. This is a tight constraint, since preliminary tests showed that, if we reduce δ, no feasible solutions can be found. For approximating the revenue obtainable by one visit at a periodic customer, we divide the total revenue of this customer by the number of required service days. All instances are publicly available (Mancini et al., 2020). After a preliminary tuning phase, the following parameter setting has been adopted for the entire experimental study, including both small and large sized instances:

Table 1
Parameter setting for MH, $MH^\star$, and ILS.

TL_{init}	10 secs
TL	10 secs
TL_{pert}	10 secs
N_{pert}	3
N_{iter}	5
N_{noimp}	5

For instances where it is not possible to find a feasible solution within TL_{init}, the initial solution is obtained by assigning all customers to their original carrier and solving the corresponding routing problem. This results into solving $|K|$ independent Consistent VRPs, each one of which is solved with a timel imit equal to TL_{init} and the best solution obtained so far is used to create a global feasible solution. Generally this time limit is sufficient to find a feasible solution, since solving a Consistent VRP is much easier than solving the CCVRP. In our computational study, all the Consistent VRPs, needed to build an initial feasible solution for the CCVRP, were solved to optimality in less than one second.

Table 2
Comparison of impact of valid inequalities. For each combination, average optimality gaps, average computational time (in seconds), and number of instances solved to the optimality are reported.

Combination	Opt.gap (%)	Time (sec)	# Opt
no valid ineq.	0.27%	2774.06	5
(21)	0.24%	2622.60	7
(22)	0.27%	2583.34	6
(23)	0.39%	2601.30	5
(24)	0.00%	426.41	10
(21) (22)	0.30%	2435.86	6
(21) (23)	0.21%	2549.67	6
(21) (24)	0.00%	276.48	10
(22) (23)	0.32%	2658.74	5
(22) (24)	0.00%	425.65	10
(23) (24)	0.00%	315.97	10
(21) (22) (23)	0.31%	2726.48	4
(21) (22) (24)	0.00%	227.69	10
(21) (23) (24)	0.00%	194.23	10
(22) (23) (24)	0.00%	371.44	10
(21) (22) (23) (24)	0.00%	262.57	10

5.1. Impact of valid inequalities

In the first part of our computational study, we analyse the impact of the proposed valid inequalities (see equations (21)-(24) in Section 3.2).

In order to find the best setting of valid inequalities, we solve the small-size instances with each possible combination of valid inequalities including a setting where no valid inequality is used. For each combination, a time limit of 3600 seconds is imposed. In Table 2, we report average optimality gaps as well as average computational times for each combination. Table 3 shows detailed results (i.e. optimality gap and computational time for each instances), if (i) no valid inequalities, and (ii) the most effective combination (21),(23) and (24) is used. The optimality gap is computed as $(UB - LB)/LB$ where UB and LB are the values of the best feasible solution found within the time limit and the best lower bound obtained so far, respectively. It is worth noting that, inequalities (24) used individually or in combination with other inequalities, allow to solve all the instances to optimality; combining them with (21) and (23) allows to further reduce computational times.

We observe that all valid inequalities have a positive impact on solution quality. Without valid inequalities, we solve only 5 instances to optimality within an average computational time of 2774 seconds, while, with the best combination, (21)&(23)&(24), we are able to solve all instances within an average computational time of 194 seconds. Hence, we can conclude that the proposed

Table 3
Detailed comparison of impact of the best combination of valid inequalities: (21)&(23)&(24). For each instance, optimality gaps and computational times (in seconds) are reported.

		no valid ineq.		(21) (23) (24)	
Instance	BKS	Opt.gap (%)	Time	Opt.gap (%)	Time
pr01_20	1743.43	0.57	3600.00	0.00	274.76
pr02_20	1880.68	0.96	3600.00	0.00	330.72
pr03_20	1732.69	0.00	2144.06	0.00	75.83
pr04_20	1909.84	0.00	3139.44	0.00	130.16
pr05_20	1882.94	0.07	3600.00	0.00	100.59
pr06_20	1857.13	0.32	3600.00	0.00	222.86
pr07_20	1670.11	0.00	2858.92	0.00	207.84
pr08_20	1745.50	0.00	894.78	0.00	69.26
pr09_20	2011.08	0.82	3600.00	0.00	367.95
pr10_20	1614.74	0.00	703.45	0.00	162.36
Average	**1804.81**	**0.27**	**2774.06**	**0.00**	**194.23**

valid inequalities are very effective. Further we notice that all combinations containing (24) are able to close the optimality gap for all instances. Therefore, the impact of (24) seems to be dominant. We decided to keep valid inequalities (21)&(23)&(24) for all remaining parts of our computational study.

5.2. Comparison of solution methods

In this part of our computational study, we compare the proposed solution methods, MIP, MH, MH*, and ILS, for small instances. Since the MIP is not able to find a feasible solution when the number of customers grows up to 30, and that MH will take long computational times to explore all the possible pairs of carriers, on large-sized instances we compare only *MH*⋆ and ILS.

Results for the small instances are displayed in Table 4.

The results show that MH obtains near optimal solutions, with an average gap of only 0.05% compared to the best solution found with the MIP. This is obtained within a very short average computational time of 38 seconds against the 194 seconds required by MIP.

Since ILS contains a random component, it is run 10 times for each instance to analyze its robustness. Computational results show that, on average, ILS is able to obtain solutions with only a 0.01% gap to the best MIP solution but within an average run time of 408 seconds, while the MIP run time is significantly shorter (about 194 seconds). Nevertheless, it is worth noting that on small-sized instances, ILS often finds the optimal solution already at the beginning of the search (within 60 seconds at most) so the further perturbations, responsible for longer computational times, do not provide any further improvement.

Only MH, *MH*⋆, and ILS are able to handle large-sized instances, while the MIP approach does not even provide a feasible solution within the given time limit. Given the large number of carriers involved, exploring all the possible pairs would lead to very large computational times, therefore we decided to apply *MH*⋆ instead of MH. Since both *MH*⋆ and ILS contain a random component, they are both run 10 times with different seeds. Average results are reported in Table 5, where we indicate the value of the objective function obtained by *MH*⋆ and the percentage improvement obtained by ILS. The fact that these values are always positive means that ILS reaches better solutions on all the instances.

We observe that on the large instances, which are obviously more challenging, ILS dominates *MH*⋆ with an improvement of 1.25% on average in solution quality, while the difference in average computational time is negligible. Indeed, ILS becomes very competitive and we can observe a significant boost in terms of solution quality, with respect to *MH*⋆.

5.3. The cost of consistency, workload balance, and minimum profit

In order to obtain insights into the potential benefits of multi-period collaborations, we compare solutions obtained by ILS against the initial solution without collaboration. Additionally, we run experiments, where constraints requiring (i) consistency, (ii) workload balance, and (iii) minimum profit are dropped. Thus, constraints (2), (15), (17), and (16) introduced in Section 3 are omitted, respectively. Results are summarized in Table 6.

The results show that the average total collaboration profit is 9.00% on the small instances, and 11.05% on the large instances. In order to identify the constraints that have a considerable negative impact on the total collaboration profit, we benchmark these results against settings, where constraints requiring consistency, workload balance, and minimum profit are dropped. Interestingly, the solution quality does not increase considerably if any of these constraints are not implied. In particular, no time consistency increases the total collaboration profit by only 0.01% and 0.12% on average on the small and large instances, respectively. This confirms finding by Kovacs et al. (2014b), who show that while time consistency is generally known to be expensive there are settings where it can be obtained for relatively low additional cost. We show that for the CCVRP it comes almost for free.

When dropping service consistency, the average total collaboration profit for the small instances increases by 1.15%, while for the large instance the increase is 0.36%.

It should be noted that dropping the workload balancing constraints does not have any effect on the total profit. Thus, we can show that workload balancing can be imposed without any loss in solution quality.

Finally, requirements regarding minimum profits, see constraints (16) also have no considerable effect on the total collaboration profit. On the small instances, the solution improves by only 0.28% on average, if minimum profits are not required.

On the large instances, the improvement is again very low (0.52%).

5.4. Impact of minimum daily profit requirements

We also run experiments where daily profit violations are not permitted. Since profits are associated with the customer and not with each visit, it is not obvious how to calculate the daily profits. In our study, we split the profit into equal shares for each visit. Following this assumption, the profit associated with a customer j in period p, $\pi^\star_{jp}$, is defined as $\frac{\pi_j}{N\nu_j}$, where $N\nu_j$ is the number of periods in which j requires service, if j requires service on period p, while, if j does not require service in period p, $\pi^\star_{jp}$ is 0. According to this definition, it is possible to compute the minimum profit allowed for carrier k in period p, $R^\star_{kp}$ starting from the solution of the problem in which each carrier serves only customers initially assigned to it. Thus, constraint (16) is substituted with:

$$\sum_{j\in I}\pi^\star_{jp}Y_{jk} - \sum_{i\in N}\sum_{j\in I}c_{ij}X^{kp}_{ij} \ge R^\star_{kp} \qquad \forall k\in K, p\in P, \tag{25}$$

The results reveal that these constraints are extremely costly. When imposing them, we could not find any solution for any instance, where the coalition resulted in a positive collaboration gain. This indicates that this requirement is too binding and destroys the benefit of entering a collaboration. However, by allowing per period profit losses, while ensuring total profit gains over the entire planning horizon, i.e. considering constraints (16) instead of (25), a loss in solution quality can easily be avoided. This is a valuable managerial insight for multi-period collaborations.

In order to obtain deeper insights into minimum profit requirements, we analyze each carrier's per period profit in a collaborative

Table 4
Comparison of solution approaches (MIP, MH, ILS) applied to small-size instances. For MIP, we report the best known solution, the optimality gap, and run times. For MH and ILS we report percentage gap to the best known solution and average run times (in seconds).

	MIP			MH		ILS	
Instance	BKS	Opt.gap (%)	Time (sec)	Gap(%)	Time (sec)	Gap (%)	Time (sec)
pr01_20	1743.43	0.00%	274.76	-0.09%	36.23	-0.02%	344.92
pr02_20	1880.68	0.00%	330.72	-0.07%	53.97	-0.04%	435.23
pr03_20	1732.69	0.00%	75.83	0.00%	22.04	0.00%	398.37
pr04_20	1909.84	0.00%	130.16	-0.09%	32.25	-0.01%	343.60
pr05_20	1882.94	0.00%	100.59	0.00%	21.41	0.00%	435.30
pr06_20	1857.13	0.00%	222.86	0.00%	69.65	0.00%	518.15
pr07_20	1670.11	0.00%	207.84	-0.04%	21.23	0.00%	369.15
pr08_20	1745.5	0.00%	69.26	0.00%	32.9	0.00%	377.30
pr09_20	2011.08	0.00%	367.95	-0.23%	51.58	-0.02%	455.39
pr10_20	1614.74	0.00%	162.36	0.00%	38.55	0.00%	406.31
Average	**1804.81**	**0.00%**	**194.23**	**-0.05%**	**37.98**	**-0.01%**	**408.37**

Table 5
Comparison of $MH^{\star}$ and ILS applied to large-size instances. We report the average objective value found by $MH^{\star}$, the average percentage improvement of ILS respect to $MH^{\star}$, and average computational times (in seconds).

	$MH^{\star}$		ILS	
Instance	Sol	Time (sec)	Improvement (%)	Time (sec)
pr01_50	4685.78	340.93	0.98	425.41
pr02_50	3861.66	305.15	1.44	312.48
pr03_50	4109.67	327.88	0.36	356.89
pr04_50	4438.26	354.19	1.14	513.34
pr05_50	4408.76	292.31	1.87	609.99
pr06_50	3986.73	349.42	1.15	706.66
pr07_50	3971.42	373.17	2.60	1080.11
pr08_50	4460.89	338.83	0.57	309.09
pr09_50	4355.95	337.97	1.49	321.12
pr10_50	4046.12	353.63	0.94	151.87
Average	**4232.52**	**337.35**	**1.25**	**478.70**

and in a non-collaborative setting. Note that in the proposed model (see Section 3) we only ensure that carriers' total individual profits (over all periods) are at least as high as their total profits outside of the coalition. In Table 7 we report the number of times, a carrier has a lower per period profit, if the carrier enters the collaboration, compared against the non-collaborative solution. We refer to this as *daily profit violations*. Additionally, we report the number of periods, where at least one carrier does not service any customer.

The results show that over the planning horizon there are several periods (i.e., days), where daily profit violations occur. Hence, individual daily profits are lower if carriers enter the collaboration compared to the non-collaborative scenario. While there is a considerable amount of daily profit losses, we observe that the number of days, where at least one carrier does not serve any customer, increases as well. We conclude that the collaborative solutions lead to several periods where vehicles are totally idle. This might give the option to gain additional profits by acting on transport spot markets.

In Fig. 1 we report a graphical representation of the optimal solution for instance *pr*01_20. This figure shows that the number of customers shared among carriers is very high. In the routing plan of day 1, we can notice that the green carrier serves 3 customers of the blue carrier and one from the violet one, while the blue carrier serves only green customers. On day 4 the red carrier, which

Table 6
Average percentage profit increase if consistency and workload balance constraints are dropped: time consistency (*no time*), service consistency (*no service*), number of customers (no balance) and minimum profit (R_k) for each carrier (*no profit*). The first column (no coll.) provides non-collaborative results, while the second column (coll.) reports the percentage improvement obtained by allowing collaboration.

Instance	no coll.	coll.	no time	no service	no balance	no profit
pr01_20	1610.41	8.26	0.02	1.58	0.00	0.29
pr02_20	1732.21	8.57	0.04	1.01	0.00	0.12
pr03_20	1548.06	11.92	0.00	0.91	0.00	0.26
pr04_20	1739.34	9.80	0.01	1.15	0.00	0.22
pr05_20	1762.73	6.82	0.00	0.98	0.00	0.08
pr06_20	1735.29	7.02	0.01	1.55	0.00	0.65
pr07_20	1538.50	8.55	0.00	1.57	0.00	0.96
pr08_20	1609.18	8.47	0.00	0.51	0.00	0.00
pr09_20	1833.93	9.66	0.02	1.40	0.00	0.02
pr10_20	1455.09	10.97	0.00	0.83	0.00	0.21
Average	**1656.47**	**9.00**	**0.01**	**1.15**	**0.00**	**0.28**
pr01_50	4261.90	11.03	0.19	0.41	0.00	1.36
pr02_50	3624.65	8.07	0.00	0.56	0.00	0.94
pr03_50	3644.96	13.15	0.24	0.41	0.00	0.41
pr04_50	4130.92	8.66	0.16	0.40	0.00	0.15
pr05_50	4085.58	9.93	0.10	0.03	0.00	0.01
pr06_50	3640.05	10.78	0.00	0.16	0.00	0.38
pr07_50	3524.39	15.62	0.14	0.24	0.00	0.09
pr08_50	4169.42	7.61	0.19	0.88	0.00	0.34
pr09_50	3838.33	15.18	0.00	0.35	0.00	0.74
pr10_50	3697.27	10.46	0.17	0.18	0.00	0.74
Average	**3861.75**	**11.05**	**0.12**	**0.36**	**0.00**	**0.52**

Table 7
Comparison of carriers' per period profits (if they collaborate) compared against non-collaborative per period profits. We report the number of times the collaborative per period profit is lower than the non-collaborative one. The right-most two columns report the number of days in which a carrier does not perform any service in the non-collaborative and in the collaborative scenarios, respectively.

Instance	Daily profit violations	No service days non-collaborative	No service days collaborative
pr01_20	7	2	2
pr02_20	9	0	1
pr03_20	7	1	3
pr04_20	6	0	1
pr05_20	6	0	2
pr06_20	10	1	3
pr07_20	7	3	0
pr08_20	5	0	1
pr09_20	8	0	3
pr10_20	7	1	0
pr01_50	19	0	1
pr02_50	22	0	7
pr03_50	12	0	9
pr04_50	21	4	11
pr05_50	12	1	10
pr06_50	10	2	11
pr07_50	19	3	9
pr08_50	21	1	10
pr09_50	13	0	10
pr10_50	11	0	7

had to serve only one remote customer, is not operating while its customer is served by another partner in the coalition.

Note that collaboration profits can be distributed among participants making use of any profit sharing method. The interested reader is referred to Guajardo and Rönnqvist (2016), where an extensive survey on profit sharing and cost allocations approaches is provided. An alternative method that distributes profits based on individual contributions is proposed by Gansterer et al. (2019). Obviously, the total collaboration profit might be reduced by payments to the provider of the centrally planned collaboration.

In summary, our study reveals that forbidding daily profit violations is extremely expensive and does not allow for successful collaborations. However, neither consistency (in time and service) nor workload balancing constraints cause a considerable increase in cost or decrease in total collaboration profit. This is a valuable managerial insight and might be a strong argument for carriers to enter collaborations, since in Pan, Trentesaux, Ballot, and Huang (2019) they are mentioned to be among the main barriers for horizontal transport collaborations.

6. Conclusion

Due to evident inefficiencies in transportation, mechanisms for sharing idle capacities are on the rise. To increase their efficiency, carriers can establish collaborations, where resources are used jointly. Thus, collaborative transportation is listed among the hot topics in logistics (Speranza, 2018).

We introduced a new multi-period VRP, where collaboration among carriers, service and time consistency as well as workload balance are simultaneously taken into account. To address this problem, we formulated a mathematical model, and proposed several valid inequalities. We were able to solve small-size instances with the model. In order to tackle larger instances, we designed an

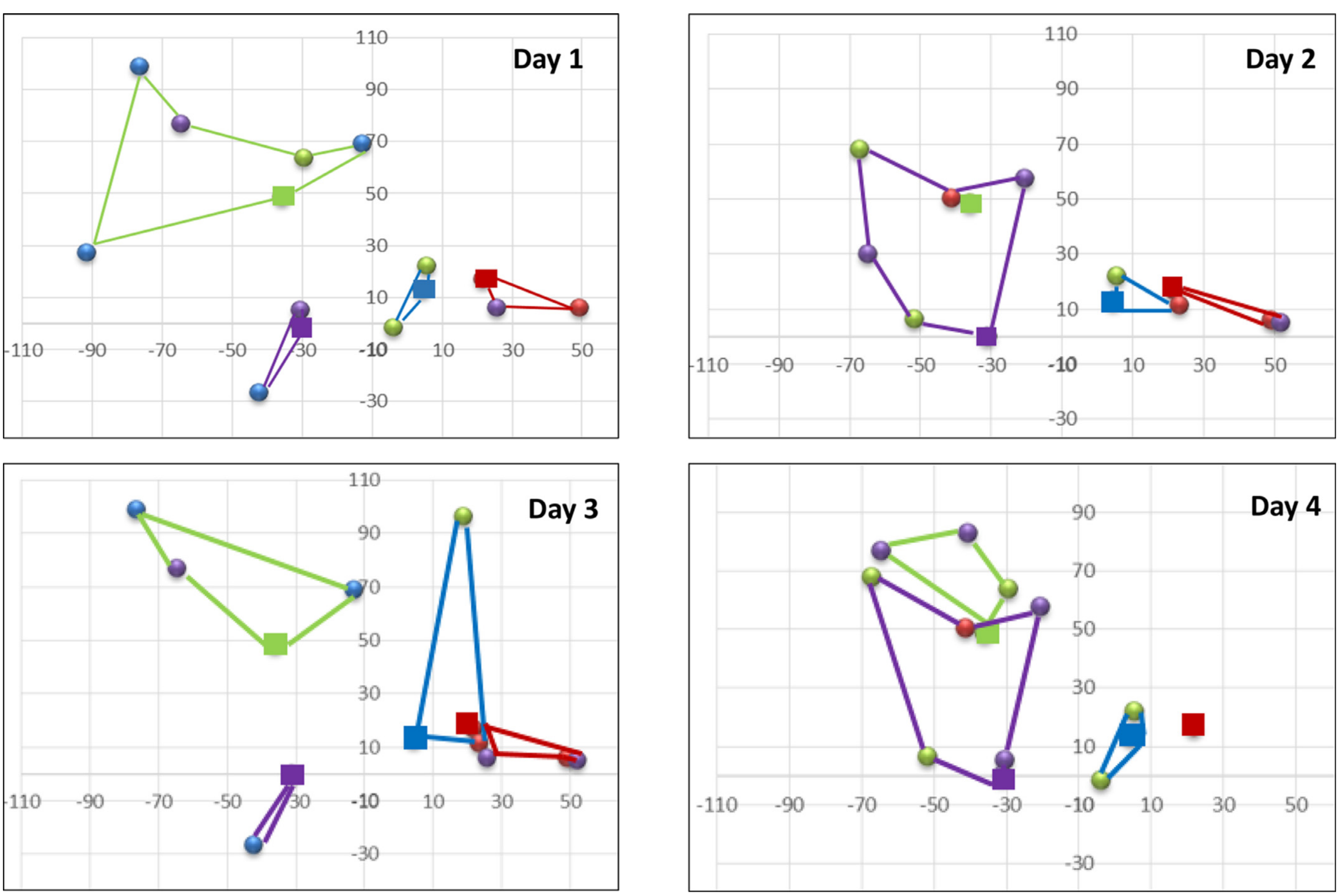

Fig. 1. Optimal solution for instance *pr*01_20. Carriers' depots are depicted as squared, customers are depicted as dots. The colour indicate the initial assignment of customers to carriers.

efficient and effective matheuristic, and an Iterated Local Search based on it. Our computational study revealed that both methods reach near optimal solutions in very short computational times.

In order to evaluate negative effects of consistency and workload balancing constraints, we ran experiments where these requirements are not considered. Our study revealed that dropping consistency constraints both for time and service, increased the total collaboration profit by less than 0.5% on average, while dropping workload balance constraints did not have any effect on the total collaboration profit. Neglecting minimum individual profits of coalition partners improved solution quality by only 0.4% on average. However, we showed that imposing constraints on minimum daily profits is very costly, and does not allow for successful collaborations. That is a valuable managerial insight for multi-period collaborations.

In summary, in our computational study we observed that both balancing and consistency requirements can be imposed with almost no additional cost, which is a meaningful managerial insight and a strong argument for carriers to enter collaborations.

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