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Multi-objective optimisation models for the travelling salesman problem with horizontal cooperation

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ABSTRACT

This paper considers a horizontal logistics cooperation in which multiple companies jointly solve their logistics optimisation problem. To capture the individual partner interests in the logistics optimisation model, we allow each individual partner to set its own set of objectives. In such a situation, the question arises whether only these individual partner objectives should be considered during the optimisation of the collaborative optimisation problem (the *partner efficiency approach*), or whether a set of coalition objectives should be defined first (the *coalition efficiency approach*). This paper investigates the merits and drawbacks of both approaches by applying them to a collaborative variant of the well-known travelling salesman problem with soft time windows (COLTSPSTW). Our results confirm that, even in a situation in which each partner has multiple, possibly conflicting objectives, joining a horizontal logistics coalition can be beneficial for all partners. We further conclude that the coalition efficiency approach is able to find good quality solutions with less calculation time, but lacks robustness. The partner efficiency approach, on the other hand, is able to provide the decision maker with a better Pareto front approximation for the individual partner interest, at the expense of a higher complexity.

1. Motivation and problem statement

Over the last decades, the transportation sector has put an enormous effort into improving the efficiency of its operations. Algorithms developed in the Operations Research community for operational transportation planning problems, most notably vehicle routing problems, have contributed considerably in reducing the number of kilometres driven unnecessarily. We refer to Braekers, Ramaekers, and Nieuwenhuyse (2016) for an elaborate overview of the current state of the art. Driven by the recent trend towards sustainable (often referred to as "green") supply chain management, the need for more efficient vehicle routing has only intensified.

Traditionally, transportation companies optimise their vehicle routes *individually*. In part due to ever more powerful optimisation algorithms, however, the potential for individual efficiency improvements have diminished and only relatively small gains remain obtainable. Researchers and practitioners therefore have increasingly searched for optimisation opportunities outside of the traditional realm of individual optimisation. One of the more promising research avenues is the *joint* or *collaborative* optimisation of transportation companies' operational activities (Cruijssen, Dullaert, & Fleuren, 2007). When different transportation companies join a so-called *horizontal logistics coalition* and agree to execute each other's transportation requests when this benefits the total efficiency of the coalition, additional opportunities for optimisation appear. A demonstration of the potential of horizontal collaboration can be grasped by considering the simple case of a company that transports a full truck of goods from point A to point B, and then—rather than driving back empty—picks up another company's products and transports them from B to A.

The main motivations for companies to engage in a horizontal logistics coalition are lower total logistics costs, improved resource and capacity utilisation, higher degree of sustainability (e.g., reduced emission of greenhouse gases and other undesirable substances), as well as an increased service level (e.g., more frequent deliveries). The existing literature on horizontal collaboration in logistics is focused mainly on proving its potential and importance (Amer & Eltawil, 2014). Furthermore, several simulation studies and pilot projects are set up in which companies execute each other's delivery requests. Efficiency gains of up to 30% have been demonstrated. We refer to Defryn, 2017 for an elaborate list of case studies. By sharing these benefits among all companies involved, a win–win situation is created. We refer to

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Leitner, Meizer, Prochazka, and Sihn (2011) for a more elaborate introduction to horizontal cooperation.

As a coalition has more opportunities for optimisation than an individual partner, collaboration in logistics is widely recognised as one of the core challenges for the immediate future (Pomponi, Fratocchi, & Tafuri, 2015). However, those opportunities need to be seized. Next to practical issues (such as finding the right partner(s), the sharing of information, legal contracts,...), this requires advanced planning algorithms. Compared to the stand-alone scenario, operational planning in a horizontal logistics coalition is considerably more complex. Partly, this is due to the size of the optimisation problem, which is obviously much larger in a horizontal cooperation. Also the higher amount of stakeholders that can have different (possibly conflicting) objectives contributes to the increased complexity. To the best of our knowledge, the latter is never considered in the existing optimisation frameworks.

The main contributions to the field of horizontal logistics cooperation with a focus on the operational optimisation problem are listed in Table 1. Using the Web of Science,[1] 59 journal publications on the topic of 'horizontal cooperation' (or 'horizontal collaboration') and 'logistics' are retrieved. Careful screening on the title and the abstract yielded a subset of 20 papers for further study. This set was extended by means of a manual search using the same keywords, resulting in a final set of 22 publications. All cited references are categorised according to the definition of the objective function in the model formulation. Four different objective functions could be identified: minimise the total distance travelled by all vehicles, minimise the total logistics cost (besides a distance-based cost, these models typically include fixed vehicle costs, time-based costs, handling costs or additional penalty costs), minimise the number of vehicles and maximise the total profit for the coalition.

We observe that in all existing approaches the logistics optimisation problem is defined at the level of the coalition, with only one global objective. In this case, the collaborative problem definition is obtained by combining all transportation requests of the individual partners into one large optimisation problem for which one or more global objective functions, which we will refer to as *coalition objectives*, are defined. As a consequence, the multi-partner context and individual partner characteristics are ignored and it is assumed that all partners agree on the set of global objectives. By adoption such an approach, the logistics planning can be optimised using any existing, non-collaborative optimisation technique. Although it is reasonable that partners in a horizontal coalition have a common goal and vision on when cooperation is successful, it should not be ignored that each individual partner remains an independent entity. Moreover, the coalition objectives are *virtual* objectives in the sense that these objectives have been defined only to solve the collaborative routing problem. For none of the partners, the coalition objectives themselves are important, but a solution will only be accepted or rejected by a partner based on the objectives of that individual partner (which we call *partner objectives*). With this paper, we are the first to propose optimisation models for logistics planning in a horizontal logistics cooperation that include individual partner objectives in the optimisation procedure.

To allow for the evaluation of all partner objectives, an allocation rule is to be defined to redistribute the obtained results at the coalition level to all individual partners. For example, if the coalition objective is to minimize total time window violation, each individual partner can easily derive the time window violation at its own customers from the overall solution. Other types of coalition objectives, most notably the total cost, time or total distance travelled cannot be trivially distributed among the partners and require an *allocation mechanism*. Several *(cost) allocation mechanisms* have been proposed in the literature, some simple (e.g., allocate the cost proportional to the amount of goods transported for each partner), other more complicated and grounded in game theory. As argued in Defryn, Vanovermeire, and Sörensen (2015), Defryn, Sörensen, and Cornelissens (2016), the cost allocation mechanism can provide an incentive for the partners to favour the coalition's objectives as it can be used as a leverage to increase the flexibility of the partners. Within the context of horizontal cooperation, a partner is considered flexible if he is willing to (partially) sacrifice his own objectives in favour of the coalition.

An important question arises whether this allocation rule and the evaluation of the individual partner objectives should be executed *after* the best solution for the coalition has been found, or *during* the search. In Vanovermeire and Sörensen (2014a), it has been demonstrated that the best solution found using the coalition objective is not always equal to the best solution found using the partner objectives, i.e., when for example the cost is divided *during* the search. In other words, when the optimisation process takes the individual partner objectives into account while looking for a good solution, the final result is generally better for all partners, at the expense of larger computing times. Vanovermeire and Sörensen (2014a) only considered the situation in which all partners have the same single objective. This paper proposes an extension to the analysis in Vanovermeire and Sörensen (2014a) for situations in which each partner may have multiple conflicting objectives.

When multiple partners, each of which having multiple objectives, jointly perform their operational planning, two options arise. A first option is that the coalition first defines a set of global coalition objectives, encompassing all objectives of all partners, then finds a solution or a set of non-dominated solutions for these global objectives, and then divides the objectives (costs) back to the individual partners. We call this approach the *coalition efficiency approach*. The second option is to consider all individual partner objectives and find a set of non-dominated solutions for each individual partner, without first aggregating them into coalition objectives. We call this approach the *partner efficiency approach*. (Fig. 1).

The main research question of this paper is to find the benefits and drawbacks of either models, and find out which one performs best. Both methods are described in more detail by applying them to the *travelling salesman problem with soft time windows* (TSPSTW). This problem has the advantage of being well-known, and has been chosen mainly for illustrative purposes. Both models, however, are generic and applicable to any collaborative planning problem.

The following Sections of this paper are organised as follows. In Section 2 we describe the TSPSTW and its collaborative variant, the COLTSPSTW. The coalition efficiency and the partner efficiency approach, are introduced in Sections 3 and 4 respectively. Afterwards, both approaches are tested on a set of collaborative TSPSTW instances. The results of these experiments can be found in Section 5. Finally, Section 6 summarises the main conclusions.

2. Case: the multi-objective travelling salesman problem with soft time windows

In this section, we first introduce the specific variant of the TSPSTW used in this paper. Then, the collaborative variant of this problem, the *collaborative travelling salesman problem with soft time windows* (COLTSPSTW), is introduced. The COLTSPSTW will be used as our explanatory example throughout the following sections of the paper.

[1] December, 2016.

Table 1
Literature review.

Reference	Objective	Description
Cruijssen, Bräysy, Dullaert, Fleuren, and Salomon (2007)	Min. total cost	The VRPTW is studied in which the sum of distribution costs of individual companies is compared to the distribution cost under joint route planning by varying multiple operational characteristics.
Krajewska, Kopfer, Laporte, Ropke, and Zaccour (2008)	Min. total distance	The single-depot PDPTW is compared to its collaborative variant, modelled as a multi-depot PDPTW. The total coalition cost is divided among the partners by using the Shapley value method after the optimisation procedure.
Berger and Bierwirth (2010)	Max. total profit	A decentralised control and auction based exchange mechanism are presented for exchanging transportation requests to facilitate collaboration among independent carriers without capacity restrictions.
Dahl and Derigs (2011)	Min. total cost	A dynamic PDVRPTW with order exchange is studied for a collaborative logistics network.
Lozano, Moreno, Adenso-Díaz, and Algaba (2013)	Min. total cost	A MILP is presented to match transportation requests of multiple companies. Different cost allocation methods are compared.
Adenso-Díaz, Lozano, and Moreno (2014)	Min. total cost	The proposed model aims to match FTL transports. The summed stand-alone scenario is compared to a merged scenario, containing all transports of all collaborating companies. The impact of different partner characteristics on the synergy is studied.
Adenso-Díaz, Lozano, Garcia-Carbajal, and Smith-Miles (2014)	Min. total cost	Considering both geographical and time compatibility, transportation requests are combined in efficient vehicle routes. The stand-alone scenario is compared to the aggregated scenario and a simulation study with varying operational characteristics is conducted.
Juan, Faulin, Pérez-Bernabeu, and Jozefowiez (2014)	Min. total distance	The savings in routing and emission costs that can be attained by backhaul-based horizontal cooperation are quantified.
Vanovermeire, Sörensen, Breedam, Vannieuwenhuyse, Verstrepen, 2014	Min. total nr. of vehicles	The cost of shipping goods on a certain lane are determined by means of a pace list. A bin packing problem is solved in which the number of required vehicles is minimised.
Wang and Kopfer (2014)	Min. total cost	A collaborative less-than-truckload pickup and delivery problem with time windows is considered. The total cost contains a fixed cost per vehicle and distance-based travel costs. A bidding system is proposed for exchanging the requests.
Flisberg, Frisk, Rönnqvist, and Guajardo (2015)	Min. total distance	The scheduling of harvest and chipping operations is studied in relation to transportation, delivered mix of assortments to customers and collaboration for transportation of wood in Sweden. An optimisation model, based on linear programming, is proposed for minimising the total (distance-based) transportation cost. Multiple cost allocation mechanisms are compared.
Li, Rong, and Feng (2015)	Max. total profit	A request exchange problem with pickup and delivery is addressed in which other carriers can bid on the shared requests.
Pérez-Bernabeu, Juan, Faulin, and Barrios (2015)	Min. total distance	An iterated local search algorithm is proposed for solving a joint route planning problem. The stand-alone scenario is modelled as a vehicle routing problem, whereas a multi-depot vehicle routing problem arises at the level of the coalition.
Wang and Kopfer (2015)	Min. total distance	A dynamic collaborative transportation planning problem for a coalition of freight forwarders serving full-truckload transport requests is studied. Two rolling horizon planning approaches are proposed.
Wang et al. (2015)	Min. total cost	To minimise the total cost in a joint distribution context, the paper establishes a model to allocate customer clusters to one of the available distribution centres in the cooperation. The Shapley value is used to allocate the obtained profits among the distribution centres.
Yang, Yang, Xia, and Liang (2016)	Max. total profit	The paper describes the joint parcel delivery by multiple cooperating logistics service providers (LSP). By adopting a collaborative distribution strategy in which each LSP only delivers those parcels that are relatively closer to its depot, the achievable profit is maximised.
Defryn et al. (2016)	Min. total cost	Both the decision on which customer to visit and their optimal sequence is modeled as a selective vehicle routing problem. Both a distance-based travel cost and a penalty for not serving some customers are considered.
Guajardo, Jörnsten, and Rönnqvist (2016)	Min. total distance	Collaboration between one or few centrally located and several peripheral companies is studied. A distance-based cost is considered when allocating each demand point to an available supply point (depot).
Hezarkhani, Slikker, and Woensel (2016)	Min. total cost	A joint route planning problem with different travel cost for driving with or without any load is considered. A global best solution is constructed that minimises the total cost for the coalition, given that certain gain sharing properties should be met.
Kimms and Kozeletskyi (2016)	Min. total distance	The authors study the cooperative travelling salesman problem (TSP) with release dates. This problem is modelled as a traditional TSP with multiple salesmen and depots.
Verdonck, Beullens, Caris, Ramaekers, and Janssens (2016)	Min. total cost	Multiple cost allocation models are compared for the cooperative carrier facility location problem. Freight transport is modelled in terms of product flows, and the goal is to open a subset of distribution centres associated with the cooperating partners and decide on the total number of product units transported from the carriers' central depots to each distribution centre and from the distribution centres to the different customer zones.
Wang et al. (2017)	Min. total cost	The multiple centres vehicle routing problem is studied as an extension of the multi-depot vehicle routing problem. Each customer is reasonably assigned to its adjacent distribution center, and goods are transshipped between distribution centres.

2.1. Stand-alone scenario: the TSPSTW

Each partner operates from its own central depot, from which goods are delivered to a set of customers in a single tour. Customer orders are assumed to be small (e.g., parcel delivery), so the vehicle's capacity will not constrain the operational planning. However, for each individual customer a time window, during which the goods should be delivered, is predefined. The underlying operational problem for every partner can therefore be modelled as a travelling salesman problem with soft time windows (TSPSTW).

We are given a complete directed graph with a set of vertices representing the depot and all customers to be served, and a set of arcs connecting these vertices. Furthermore, a service time and a time window are defined for each vertex, including the depot. The service time models the time the driver is expected to spend at the customer's location for loading, unloading, or providing service. The time window is defined by the customer's ready time and due time. Arriving at the customer's location before its ready time is allowed, although the vehicle has to wait until the start of the time window before the service can start. Arriving too late,

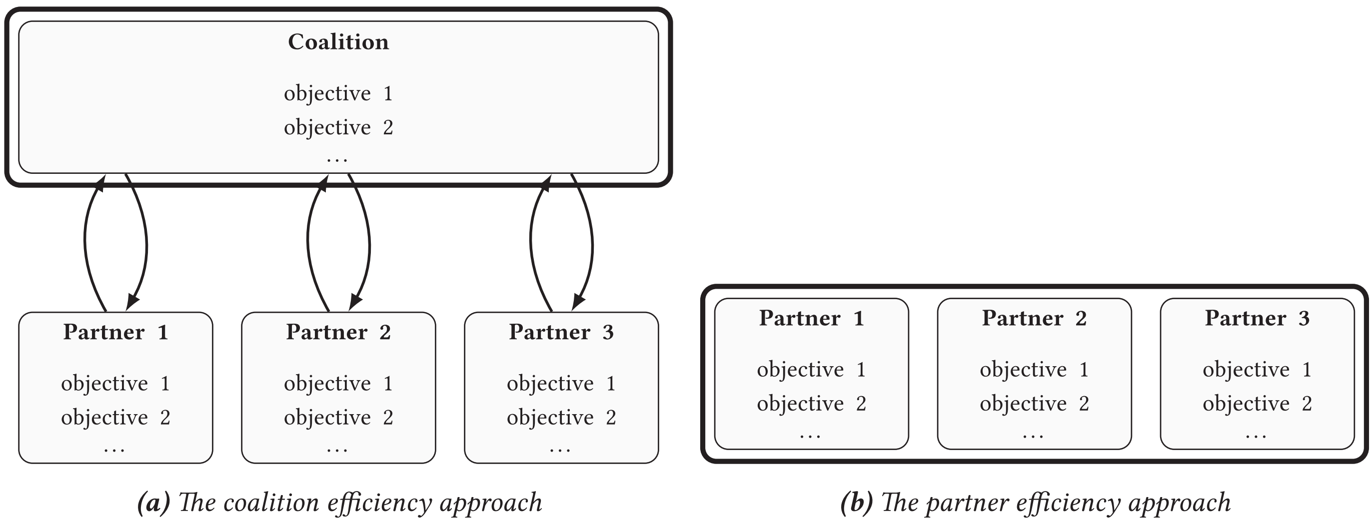


Fig. 1. Difference between the coalition efficiency approach and the partner efficiency approach. The bold box indicates where the optimisation problem is solved.

or not being able to finish the service before the due time, results in a *time window violation*. The goal is to construct a Hamiltonian cycle, a path that starts and ends at the partner's depot in which every customer is visited exactly once.

The following two objectives are considered: (i) the minimisation of the total distance travelled, and (ii) the minimisation of the time window violations over all the partner's customers. Both objectives are conflicting, in that a smaller total time window violation can be achieved at the expense of a larger distance travelled and vice versa.

The idea of soft time window can be linked directly to the concept of *flexibility* (Vanovermeire & Sörensen, 2014b). If the time windows are very strict, the degree of freedom in the planning is limited. This will result in a longer total distance travelled in order to make sure that all customers are visited on time. The more a company is able and willing to extend the time windows or allow a certain time window violation, the more freedom it creates to reduce the total travelled distance by changing the positions of the customers in the trip.

In this paper, we adopt a multi-objective approach for solving the TSPSTW and no a-priori decision is made on the relative importance of both objectives. Instead of constructing one single (optimal) solution, the aim is to generate many solutions that are Pareto-optimal with respect to both objectives. We leave it to the decision maker to select the most preferred solution from this set, based on other criteria. This decision is however out of the paper's scope.

2.2. Collaborative scenario: the COLTSPSTW

We consider a horizontal cooperation in which multiple companies jointly optimise their logistics operations. A two-partner example is visualised in Fig. 2. In this figure, the partner's depots are denoted by the squares and the circles represent the customers. For visualisation purposes, only the total distance minimisation objective is considered here. The logistics planning problem for each individual partner is modelled as a TSPSTW. From the moment that *geographic similarity* (the degree of overlapping geographic coverage between the cooperating partners) exists, it is likely that synergies can be exploited by allowing certain customers to be served by another partner's vehicle (Raue & Wallenburg, 2013). The collaborative problem that appears at the level of the coalition is a *multi-depot multi-travelling salesman problem with time windows*. This problem is closely related to the multi-depot vehicle routing problem. We refer to Montoya-Torres, Franco, Isaza, Jiménez, and Herazo-Padilla (2015) for an extensive literature review on this problem. However, no customer demands are considered and the vehicles do not have any capacity restrictions in our problem formulation. Therefore, the problem studied in this paper is denoted as the *collaborative travelling salesman problem with soft time windows* (COLTSPSTW).

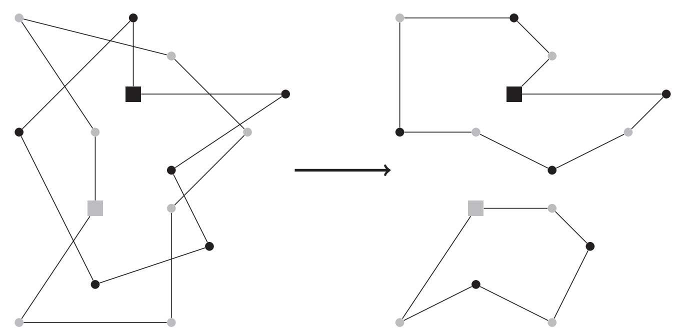


Fig. 2. The collaborative travelling salesman problem with soft time windows for a two-partner (black and grey) horizontal cooperation.

In this paper, it is explicitly not questioned how the coalition is formed and how the partners deal with organisational, legal or IT-related issues. We assume the collaboration is set up and all partners agree on a system to share information and orders, and that a cost allocation method is selected to divide the total cost of the coalition among the individual partners.

The main remaining question is which objective(s) to use when solving the COLTSPSTW. A first approach assumes that all partners agree on a common goal and are able to define a set of global coalition objectives. Based on the stand-alone scenario and the similarity between the individual partners, we suggest the following two coalition objectives: (i) the minimisation of the total distance travelled, and (ii) the minimisation of the summed time window violations over all customers. As a result, we consider the coalition to be a single entity and the fact that customers belong to different companies has no importance any more. We say that we optimise towards *coalition efficiency*, i.e., make the coalition as a whole as efficient as possible. This idea forms the basis for the *coalition efficiency approach*, described in Section 3.

A second approach acknowledges that all partners remain independent companies that have individual objectives. We assume

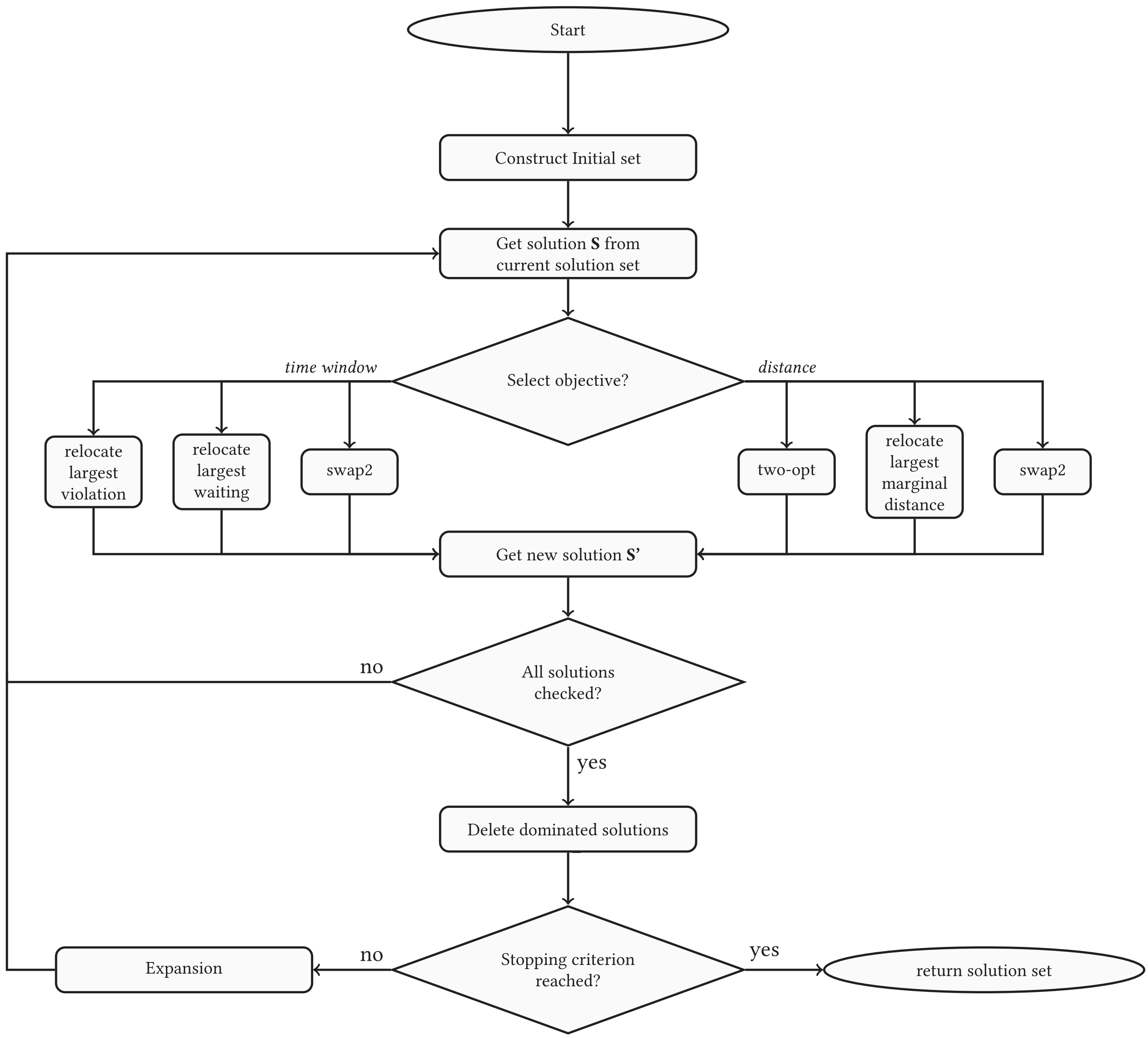


Fig. 3. Visualisation of the developed heuristic to solve the collaborative travelling salesman problem with soft time windows at the coalition level.

that each partner aims to: (i) minimise the summed time window violations *of its own customers*, and (ii) minimise its own *allocated share* of the total logistics cost. A solution that is acceptable for one partner (i.e., it is in the Pareto set for this partner's objectives) may not be so for the other partners. A good solution for the coalition should therefore be a compromise with respect to all individual partner objectives, and should be in the Pareto sets of all partners in the coalition. In this case, we talk about optimisation with respect to *partner efficiency*. We will elaborate on this idea in Section 4.

3. Coalition efficiency approach

A solution is considered *coalition efficient* if it is in the Pareto set of non-dominated solutions with respect to the coalition objectives. Based on this idea and the collaborative vehicle routing approach proposed by Defryn et al. (2016), the coalition efficiency approach consists of four steps.

- **Step 1:** Aggregate and redefine the logistics problem at the level of the coalition.
- **Step 2:** Construct an efficient solution set for the coalition as a whole.
- **Step 3:** Project the solutions obtained during step 2 on the individual partner objectives using predefined allocation rules.
- **Step 4:** Evaluate the Pareto-efficiency of each solution according to each of the partner objectives. Only solutions that are marked as efficient by every partner are kept in the final solution set of the collaborative problem.

In the following sections, we will elaborate more on each step of the coalition efficiency approach by applying it to the colt-spstw.

3.1. Step 1: aggregation

The goal of this first step is to redefine the logistics problem at the level of the coalition. All transportation requests, networks

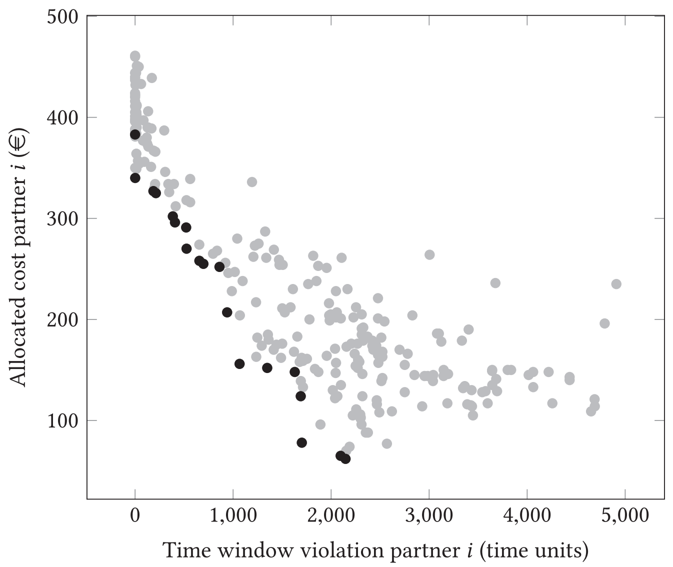


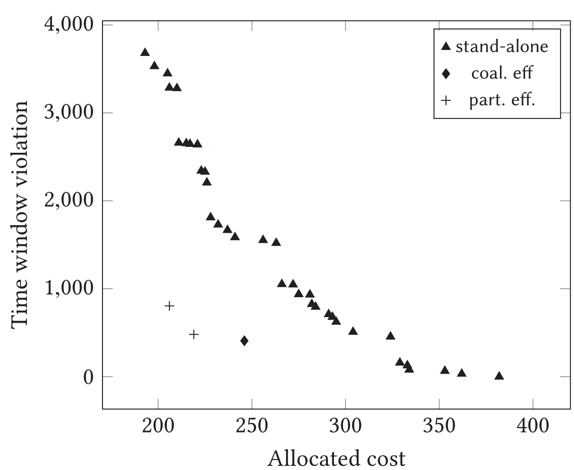
Fig. 4. The allocated cost in function of the corresponding time window violation for one single partner in the coalition. All solutions on the Pareto frontier of the coalition are visualised by the dots. The solutions that are efficient for partner i are highlighted in black.

and available resources of the individual partners are aggregated into one optimisation problem. To determine the objective function of the coalition, it is assumed that all collaborating partners agree on a single set of coalition objectives. In this way, the multi-partner logistics problem is transformed into a traditional, non-collaborative one. Similar to the stand-alone scenario, the coalition objectives for the COLTSPSTW are considered to be (i) the minimisation of the total distance travelled by all vehicles (total coalition cost), and (ii) the minimisation of the total time window violation over all customers.

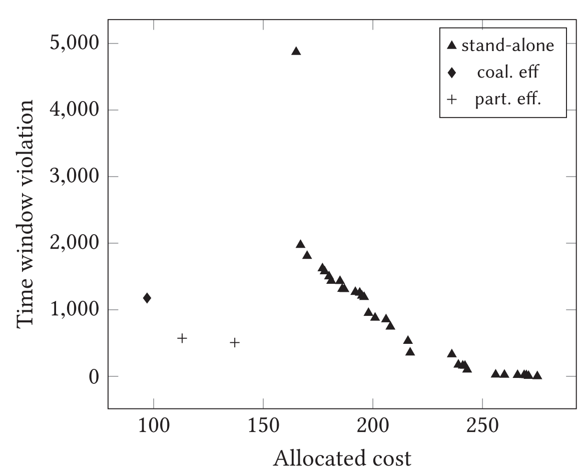
In our definition of the COLTSPSTW, the partners are homogeneous, i.e., they have the same set of objectives. This is, however, not a requirement of the coalition efficiency approach. In general, any combination of partners can be considered, as long as a common set of objectives can be negotiated. This, however, will become more difficult in practice for diverging partner objectives.

3.2. Step 2: optimisation at the coalition level

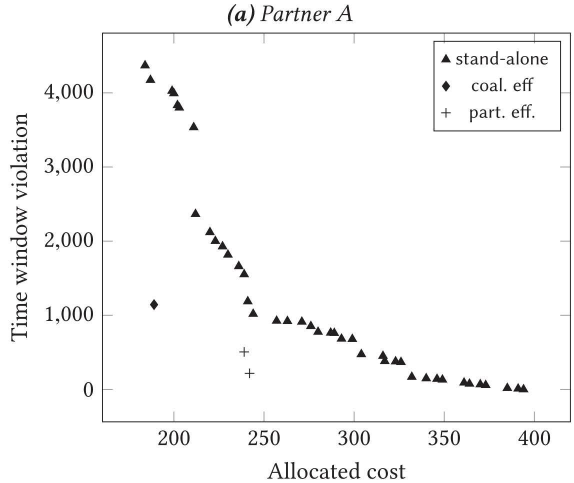
During the second phase, the aggregated model defined in step 1 is solved by using any available non-collaborative logistics optimisation technique. As two coalition objectives are identified for the COLTSPSTW, a multi-objective optimisation method is required. Because we explicitly do not want to make any assumptions on the importance nor weight of each objective function, the method of *posteriori preference articulation* is used in this paper, which will



***(a)** Partner A*

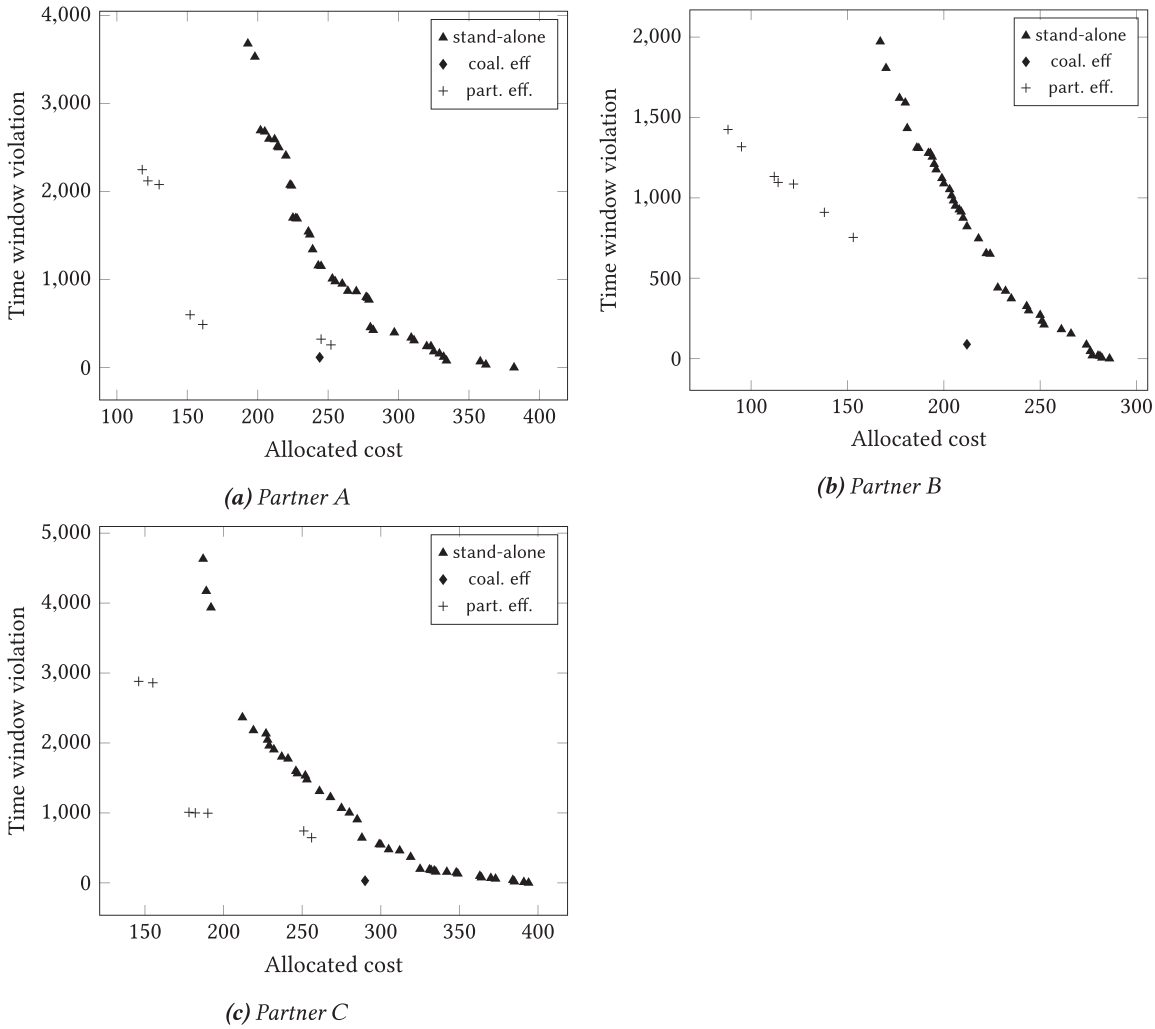


***(b)** Partner B*



***(c)** Partner C*

Fig. 5. Solutions for the C1 instance.



(a) Partner A

(b) Partner B

(c) Partner C

Fig. 6. Solutions for the C2 instance.

Table 2
Construction strategies.

Strategy	Definition
NEAREST NEIGHBOUR	Start from an unused depot and iteratively add the closest unvisited customer to the trip. An equal number of customers is added to each trip.
SORTED BY READY TIME	Add all customers from a single partner to a trip and sort them according to their ready time.
SORTED BY DUE TIME	Add all customers from a single partner to a trip and sort them according to their due time.

return a Pareto set (Veldhuizen & Lamont, 2000). In what follows, we propose a multi-directional local search metaheuristic, based on the idea of Tricoire (2012).

3.2.1. Metaheuristic overview

A visualisation of the solution procedure is given in Fig. 3. First, an initial solution set is constructed by the algorithm. Three different construction strategies are used to diversify the initial solutions: *nearest neighbour*, *sorted by ready time* and *sorted by due time* (see Table 2). Afterwards, each solution is improved with respect to each objective individually by means of local search.

The improved solution S' either dominates S or both solutions can be Pareto-efficient. After having improved all initial solutions, the dominated solutions are discarded and the search continues with all non-dominated ones. In this way, we also allow the size of the Pareto frontier to increase/decrease. When the stopping criterion is met, the current Pareto frontier is returned by the algorithm.

3.2.2. Neighbourhood structures

To improve the current solution S, the multi-directional local search metaheuristic uses five different neighbourhoods. We refer to Table 3 for a complete overview. Depending on the current objective (columns TW and Dist), different neighbourhoods are available from which one is selected at random every iteration. A first improvement search strategy is used.

3.2.3. Expansion

At the end of every iteration, an *expansion operator* is called. As the current solution set represents the best Pareto frontier approximation found so far, we expect that high quality solutions can be found in the close neighbourhood of the solutions in this set. By including for every solution an extra random neighbour from its SWAP2 neighbourhood (see Table 3), the number of solutions in the set is doubled. In this way, more opportunities for further improvement are created and additional diversification is added to the set.

Table 3
List of different neighbourhoods, embedded in our metaheuristic for the coalition efficiency model.

Neighbourhood	TW	Dist	Definition
RELOCATE-VIOLATION	✓		Remove the customer with the largest time window violation from the solution and insert it before the customer with the largest waiting time.
RELOCATE-WAITING	✓		Remove the customer where the vehicle has to wait the longest time from the solution and insert it after the customer for which the due time is closest to the ready time of the customer to be inserted.
RELOCATE-MARG-DIST		✓	Remove the customer with the highest marginal distance from the solution and insert it at the position where it causes a minimal insertion cost.
SWAP2	✓	✓	Swap the position of two customers in the solution.
TWO-OPT		✓	Remove two edges and replace them by two new edges to close the tour.

3.3. Step 3: projection on the individual partner objectives

As the coalition is not able to further improve without worsening the value of at least one coalition objective, all solutions returned by step 2 are coalition efficient. This, however, does not imply that all obtained solutions are also efficient for each partner. To evaluate the Pareto-efficiency of the solutions on the partner objectives, the coalition objectives need to be redistributed to the partners.

For the time window violations this is straightforward. In order to obtain the total time window violation assigned to a partner, the violations over all customers of this partner are summed. However, in order to know which part of the total coalition cost should be allocated to the individual partners, a *cost allocation method* is necessary. All experimental results discussed in Section 5 are obtained by applying the *Shapley value cost allocation method* (Shapley, 1953), as it is put forward as best practice in horizontal logistics cooperation due to its desirable properties (Biermasz, 2012). For more details on the Shapley value method and its implementation in the experiments, we refer to Appendix A.

3.4. Step 4: evaluation

When projecting the obtained results on the individual partner objectives in step 3, we expect a negative correlation between the allocated cost and the corresponding time window violation for each partner. This means that for solutions in which the partners have to tolerate a large time window violation, we expect a lower cost to be allocated to this partner. This is explained by the fact that less strict time windows give rise to more efficient solutions in terms of cost. On the other hand, if a partner is more rigid by only allowing very small time window violations, we expect him to pay a higher part of the corresponding total coalition cost. This trend can also be seen in Fig. 4, in which every point represents an efficient solution for the coalition.

Fig. 4 shows clearly that not all coalition-efficient solutions are on the Pareto frontier for the individual partner objectives, which is highlighted in black. The dominated solutions, denoted in grey, are unlikely to be accepted by the current partner. After having repeated this for every partner, only the solutions that are accepted by all partners are kept as good candidate solutions for the coalition. This approach, however, does not guarantee that the set of candidate solutions is non-empty.

4. Partner efficiency approach

The coalition efficiency approach, discussed above, has the following drawbacks. First, it requires the coalition to be able to define a global set of objectives, which can be challenging if the interests of the partners differ significantly. Also, it is not guaranteed that all solutions that are efficient for all individual partners belong to the Pareto set of non-dominated solutions at the coalition level. This means that a solution might be efficient for all collaborating partners, but not for the coalition. These solutions are not found by the coalition efficiency approach. Conversely, we showed that there is no guarantee that a solution that is efficient with respect to the coalition objectives is on the individual Pareto frontier. In some cases, the intersection of the solutions projected onto the Pareto frontiers for the individual partners might even be empty.

To overcome these issues, we propose an alternative approach that integrates the individual partner objectives directly into the optimisation procedure: the *partner efficiency approach*. In the following sections, the method is presented. Again, the COLTSPSTW is used as our explanatory example.

4.1. Objective functions

For every partner, both partner objectives defined in Section 2.2 are considered directly as an objective function in the logistics optimisation model. This implies that a cost allocation method should be *integrated in the objective function of the solution procedure for the operational planning itself* to determine the value of the cost objective.

Solutions will only be retained if they are efficient for every partner. However, it is likely that solutions with a lower total distance (cost) or time window violation are beneficial for at least one (in best-case: most) of the partners. Therefore, these objectives are also added to the model. Although only the individual partner objectives are used to evaluate the current solutions, these additional objectives might guide the search towards the more interesting parts of the solution space. In this way, we try to reduce calculation time by avoiding the exploration of solutions that are far from optimal.

To summarise, four different types of objective functions can be identified in our model formulation (see also columns 2–5 in Table 4): the minimisation of the time window violations for partner i (TW_i), the minimisation of the cost allocated to partner i ($Cost_i$), the minimisation of the total time window violation (TW) and the minimisation of the total distance driven (Dist). Compared to the coalition efficiency approach, the number of objectives in the partner efficiency approach will be high. This high dimensionality is expected to increase the complexity of the model significantly.

4.2. Metaheuristic solution approach

Similar to the coalition efficiency approach, a multi-directional local search metaheuristic is used to tackle the multi-objective COLTSPSTW. To allow as much as possible a fair comparison of the two approaches, an attempt was made to maximize the similarity between both metaheuristics. Although the basic structure of the algorithm remains unaltered, a slightly different approach is required at some points during the search. We will highlight these differences in the following sections.

Table 4
List of different neighbourhoods, embedded in our metaheuristic for the partner efficiency model.

Neighbourhood	**TW$_i$**	**Cost$_i$**	TW	Dist	Definition
RELOCATE-VIOLATION	✓		✓		Remove the customer with the largest time window violation from the solution, and insert it before the customer with the largest waiting time.
RELOCATE-WAITING	✓		✓		Remove the customer where the vehicle has to wait the longest time from the solution, and insert it after the customer for which the due time is closest to the ready time of the customer to be inserted.
RELOCATE-MARG-DIST				✓	Remove the customer with the highest marginal distance from the solution, and insert it at the position where it causes a minimal insertion cost.
RELOCATE	✓	✓			Remove one customer from the solution, and insert it again in the solution at the position where it improves the current objective the most.
SWAP2	✓	✓	✓	✓	Swap the position of two customers in the solution.
TWO-OPT		✓		✓	Remove two edges and replace them by two new edges to close the tour.

4.2.1. Neighbourhood structures

Our metaheuristic makes use of six local search neighbourhoods to handle the four different types of objective functions in the model. Some of these neighbourhoods are constructed for one specific objective (e.g., the RELOCATE-VIOLATION neighbourhood focuses on time window violation minimisation) while others are more general (e.g., SWAP2 and RELOCATE). For a complete overview, we refer to Table 4.

4.2.2. Solution evaluation

To evaluate a candidate neighbour solution with respect to the individual partner objectives, the projection on the individual partner objectives of the time window violations and the total cost should be calculated. This means that n two-dimensional Pareto frontiers (such as the graph shown in Fig. 4) should be maintained during the search for an n-partner coalition.

While running the optimisation procedure, we make use of a *weak domination rule*. This rule states that every solution that is part of the current Pareto frontier of at least one partner, is kept in the solution set. In this way we allow the algorithm to improve the solution further for the other partners during the following iterations.

A *strong domination rule* is used in two situations: when (i) the stopping criterion is reached and if (ii) the total number of solutions in the pool reaches a predefined threshold value. As each iteration all solutions–objective combinations are explored by the algorithm, the latter ensures that the calculation time per iteration remains reasonable. The strong domination rule disregards all solutions that are not in the intersection of all individual Pareto frontiers and, consequently, only solution that are efficient for *all* partners in the coalition are kept.

5. Computational experiments

Both approaches discussed in this paper, are implemented in C++ and tested on a set of benchmark instances from the TSPSTW literature. All computational results are obtained using an Intel(R) Core(TM) i7-4790 @ 3.60 gigahertz and 16 giga bytes of RAM.

5.1. Benchmark instances

For our experiments, we used the benchmark instances provided by Dumas, Desrosiers, Gelinas, and Solomon (1995) as the input for all the stand-alone scenarios. In other words, a coalition of multiple partners is represented by a *combination of multiple existing benchmark instances*. In order to prevent the aggregated instances from becoming too large to solve them in a reasonable amount of time, we limit the experiments to the small instances with 20 customer nodes. The aggregated three-partner instances therefore contain 60 customer nodes and eight objectives from which two at the coalition level and two for each individual partner. Four different coalitions are simulated, based on the combination of instances shown in Table 5. The instance are named as follows: *n[number-of-customers]w[time-window-width].[id-number].txt*.

Table 5
Construction of the benchmark instances. Every three-partner coalition is formed by combining three stand-alone instances from the TSPSTW literature.

Coalition id	Partner A	Partner B	Partner C
C1	n20w20.001.txt	n20w20.002.txt	n20w20.003.txt
C2	n20w40.001.txt	n20w40.002.txt	n20w40.003.txt
C3	n20w60.001.txt	n20w60.002.txt	n20w60.003.txt
C4	n20w80.001.txt	n20w80.002.txt	n20w80.003.txt

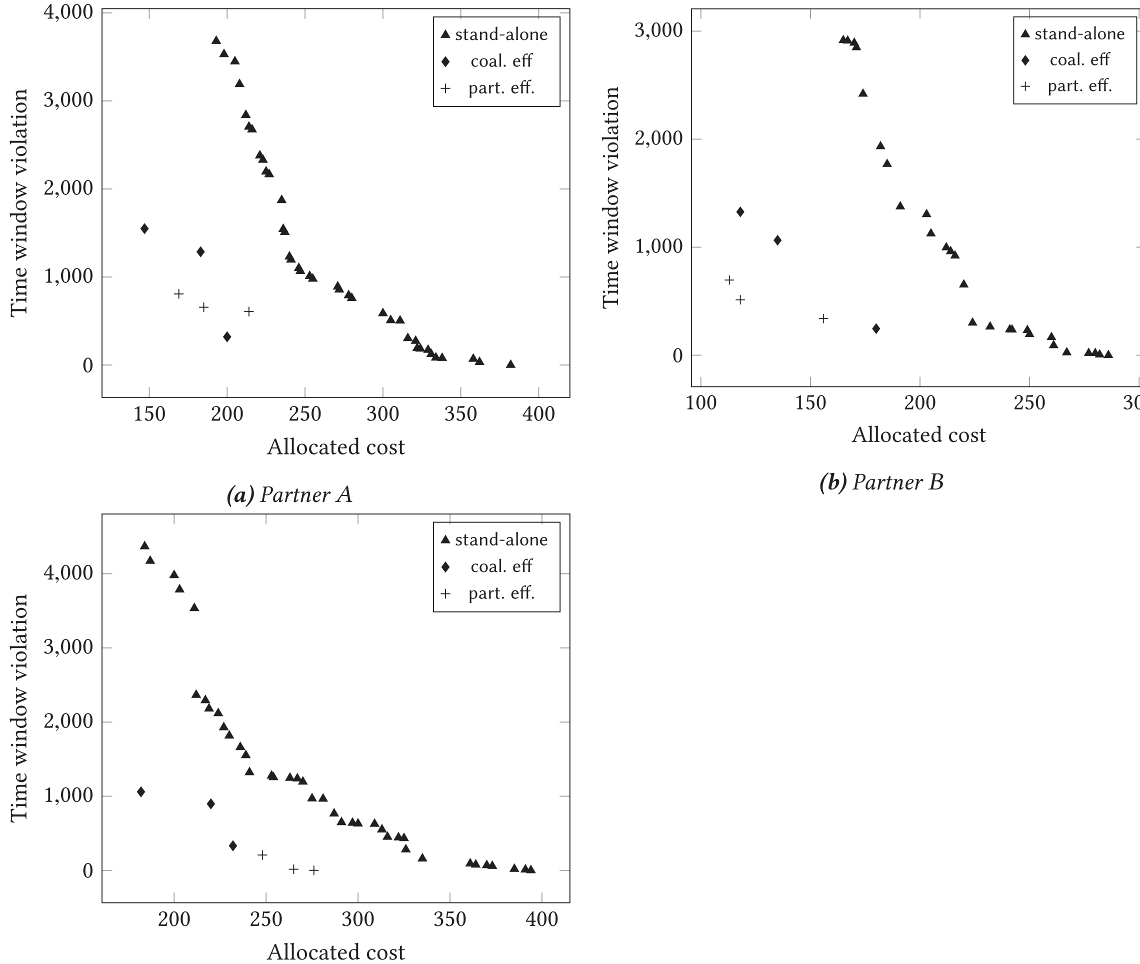
5.2. Stopping criterion

To allow a fair comparison between the two methods and the results obtained for sub-coalitions of different sizes, we will use a predefined number of iterations as the stopping criterion. In each iteration, we try to improve every solution in the current Pareto set with respect to every objective function in the model. In other words, a new iteration is initiated every time the expansion operator is called. The required calculation time will therefore vary significantly according to the model complexity and the instance size. In what follows, the maximal number of iterations is set to 100.

5.3. Simulation results

All obtained results for the coalition efficiency approach and the partner efficiency approach are visualised in Figs. 5–8 and summarised in Table 6. In all figures, the stand-alone scenario is obtained by solving the (non-collaborative) travelling salesman problem with soft time windows for each individual partner separately (see also Section 2.1). The main conclusions are discussed in this section.

First, we can conclude that engaging in a horizontal cooperation is profitable for all partners in the simulated coalitions. All solutions returned by both the coalition efficiency approach and the partner efficiency approach dominate the stand-alone solutions. This means that a reduction in both total cost and time window violation is realised for all partners through horizontal cooperation.



(a) Partner A

(b) Partner B

(c) Partner C

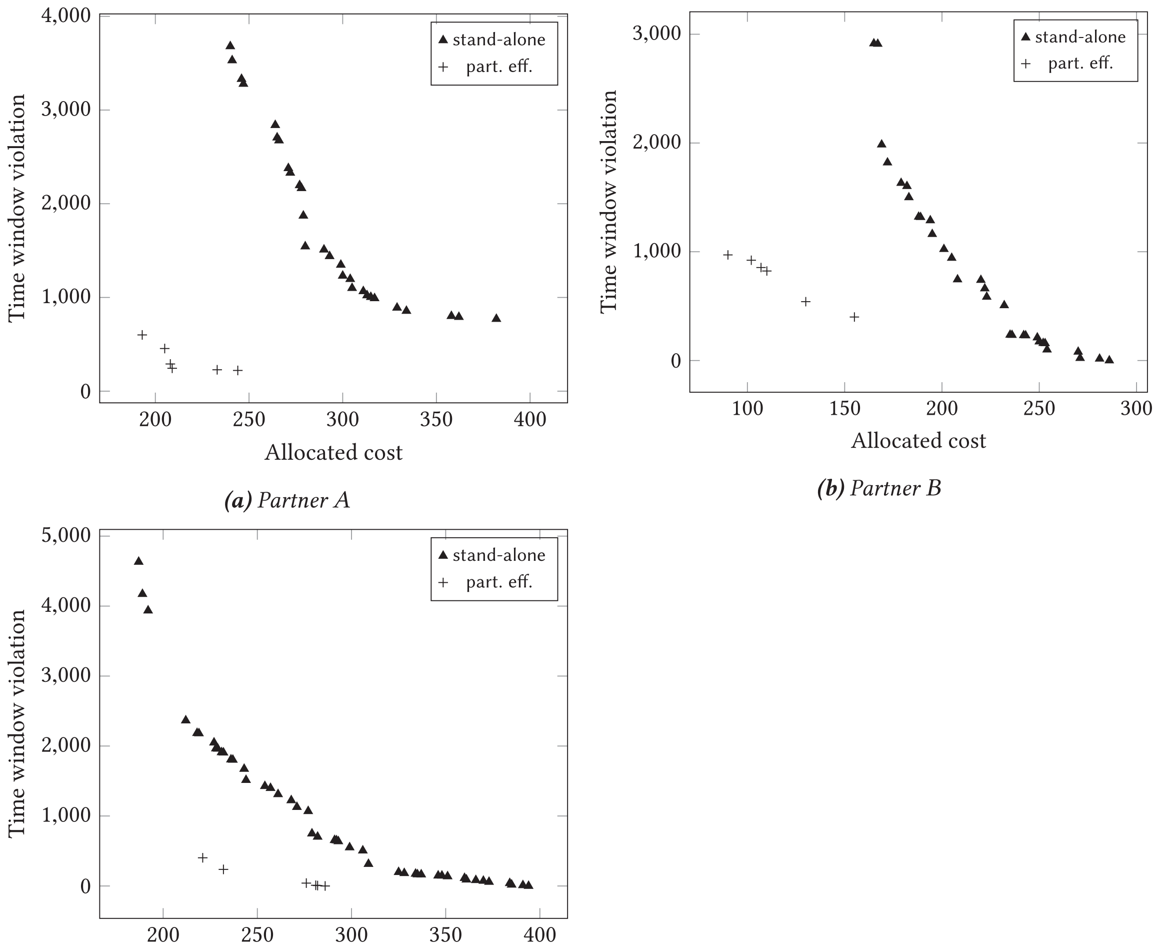
Fig. 7. Solutions for the C3 instance.

Table 6
Overview of all simulation results for 100 iterations.

	Coalition efficiency model					Partner efficiency model			
	Calculation time (s)			Results		Calculation time (s)			Results
	1 partner	2 partners	3 partners	#CE-sol	#sol	1 partner	2 partners	3 partners	#sol
C1	1.09	6.40	25.02	92	1	2.71	185.71	1777.86	2
C2	1.04	7.52	29.22	97	1	3.04	190.30	990.43	7
C3	0.95	7.38	29.72	56	3	2.90	172.81	1761.75	3
C4	0.96	7.37	25.64	95	0	3.06	202.66	2288.37	6
Average	1.01	7.17	27.40			2.93	187.87	1704.60	

Furthermore, in Table 6, the number of coalition-efficient solutions found in step 2 of the coalition efficiency approach is given in column '#CE-sol'. From this set, the number of solutions on the efficient Pareto frontier of all partners is given in column '#sol'. It can be concluded that a feasible solution is found for three out of four simulated coalitions. For coalition C4, none of the coalition-efficient solutions was non-dominated with respect to all individual partner objectives. Compared to the partner efficiency approach, only a limited number of solutions is returned by the coalition efficiency approach.

This might be due to the fact that the *efficiency of the coalition* is the main goal in the coalition efficiency approach. Solutions are therefore only constructed according to the objectives defined at the coalition level. It is only after the optimisation, in steps 3 and 4, that the obtained solutions are evaluated by the individual partners and removed if not efficient. It should be acknowledged that finding a good intersection for all individual partners' objectives during the evaluation phase is a matter of luck, as these individual objectives are not taken into account while constructing the solution set at the coalition level. Therefore, there exists a large discrepancy between the direction in which the optimisation is executed, and the way the final solutions are evaluated. Also, the Shapley value cost allocation mechanism, used for the computational experiments, relies on the solution set found for *every possible sub-coalition of the coalition*, which therefore has to be simulated as well. A small change in one of these sub-coalition Pareto frontiers might result in a different evaluation of the current solutions at the coalition level.



(a) Partner A

(b) Partner B

(c) Partner C

Fig. 8. Solutions for the C4 instance.

The partner efficiency approach tends to provide a better approximation of the underlying Pareto frontiers. The reason is twofold. First, by not limiting the search to only solutions that are Pareto-efficient at the coalition level, additional solutions are found by using the partner efficiency approach that will never be considered by the coalition efficiency approach. Second, the optimisation problem is solved directly at the individual partner level, without introducing the aggregation step towards the coalition level. As a result, the evaluation of potential solutions is in line with the optimisation procedure itself. The partner efficiency approach is therefore able to provide the decision maker with a more complete view on the trade-off between the different individual partners' objectives. This strength is also its biggest drawback as due to the growing number of objectives, the computational complexity of the model increases significantly, resulting in larger calculation times. The average calculation time for all sub-coalitions of different sizes is also shown in Table 6.

6. Concluding remarks and further research

The recent trend of horizontal cooperation in logistics receives increasing attention as it can yield some major advantages. Because of a more efficient operational planning, transportation companies are able to reduce the total logistics cost, while maintaining high service levels. From an operational perspective, however, horizontal cooperation requires existing models to be revised in order to comply with a multi-partner collaborative environment. This paper can be considered as a first, exploratory step towards more integrated methods for operational optimisation in a multi-partner context.

In this paper, we introduced the concepts of *coalition efficiency* and *partner efficiency* to acknowledge a difference in priorities and goals between all collaborating partners, and between the group and the individual players. We have used these definitions to construct two new solution approaches for solving a multi-objective collaborative transportation problem: the *coalition efficiency approach* and the *partner efficiency approach*. Both approaches aim at providing the decision makers with a solution set by focusing not only on the performance of the group but also on the individual objectives of each partner.

To ensure that the total coalition cost is divided properly among all collaborating partners, both models aim at integrating a cost allocation mechanism into the optimisation procedure. In the coalition efficiency approach, this is done sequentially after an aggregated logistics plan is constructed for the coalition as a whole. The partner efficiency approach on the other hand, combines the operational planning and the cost allocation method into one optimisation problem. Although this integration might guide the search into a more desirable direction during the optimisation phase, it will increase the complexity of the model exponentially.

The coalition efficiency approach is able to generate good quality solutions in relatively short calculation times. However, due to the fact that the optimisation is executed at coalition level where afterwards solutions are evaluated on the partner level objectives, only a very limited number of solutions is returned by the algorithm. The fact that an efficient solution at the coalition level is also efficient at individual partner level can be considered a matter of "luck". The partner efficiency approach, on the other hand, provides the decision maker with a more complete Pareto frontier approximation, allowing a better understanding of the underlying trade-offs between the different objectives of the individual partners. Because of this reason, we prefer the partner efficiency approach as all individual partner objectives are included explicitly in the optimisation procedure. This is, however, at the expense of very high calculation times, compared to the coalition efficiency approach.

As both models possess advantageous properties, a promising opportunity for further study would be the integration of both ideas. The aim of that integrated model should be finding a balance between the objectives at coalition and partner level. The computational experiments conducted in this paper were limited to small instances, mainly used to show the working of the developed solution models. To study the impact of varying partner characteristics on the solutions obtained by both approaches in more detail, a large-scale simulation experiment should be conducted. This is, however, left for future research. Furthermore, we aim to integrate different cost allocation methods into the suggested models and study the impact of these methods on the obtained solution set. Finally, the integration of more qualitative techniques for the evaluation and comparison of multi-objective solution spaces (e.g., the hypervolume, measures of spacing and spread,...) might improve the overall quality of the obtained Pareto frontiers by guiding the search even more in a desirable direction.

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Appendix A. Algorithmic implementation of the Shapley value

A1. Definition

In both models described in this paper, a cost allocation method is assumed to be selected by the collaborating partners to properly divide the total coalition cost. In our computational experiments, we chose for the *Shapley value cost allocation method* (Shapley, 1953).

The result of this game theoretical approach is determined by playing a cooperative game (N, C), where N represents the coalition with n collaborating players (partners), and C the *characteristic function* (Zolezzi & Rudnick, 2002). This characteristic function is defined by the cost of *all possible sub-coalitions* S, with $S \subseteq N$. The cost allocated to partner i, denoted by ψ_i, is defined according to the following formula.

$$\psi_i = \sum_{S \subseteq N \setminus i} \frac{|S|!(|N| - |S| - 1)!}{|N|!} (c(S \cup i) - c(S))$$

A2. Algorithmic implementation

The characteristic function requires the total coalition cost for every sub-coalition $S \subseteq N$ to be known. However, the solution set for a sub-coalition is represented by a Pareto frontier in which each solution has a different total cost. Therefore, obtaining *the* cost for a sub-coalition is not straightforward. To allow a fair comparison of the cost of two solutions from different sub-coalitions, we introduce the idea of *constant flexibility*. This idea assumes that the attitude of a partner towards flexible behaviour is independent of the coalition configuration.

Table A.7.
Binary-to-integer conversion of all sub-coalitions for a three-partner coalition.

Integer	Binary	Integer	Binary
1	0 0 1	5	1 0 1
2	0 1 0	6	1 1 0
3	0 1 1	7	1 1 1
4	1 0 0		

Consider the following example for a two-partner coalition. The collaborative solution for which we want to allocate the total cost induces a time window violation of 200 and 500 for partner 1 and partner 2 respectively. To calculate the Shapley value, the stand-alone cost of each partner should be known. As the stand-alone scenario of each individual partner is represented by a Pareto frontier, the cost from the stand-alone solution that corresponds to a time window violation of 200 is taken for partner 1. A similar approach is used to determine the stand-alone cost of partner 2. In this way, it is assured that the difference in cost for the two solutions are based solely on the difference in coalition configuration as the values on the time window violation objective are equal.

To include the Shapley value in the partner efficiency approach, an *integer–to–binary conversion* is used. Each sub-coalition is labelled by an integer ranging from 1 up to $2^n - 1$, for an n-partner cooperation. The composition of a sub-coalition (stating if a partner is a member of this sub-coalition or not) is obtained by the corresponding binary representation. For a three-partner coalition, the different sub-coalitions are simulated in the order shown in Table A.7. In this way it is ensured that all (sub)coalitions can rely on the results of their sub-coalitions.

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