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To team up or not: single versus team driving in European road freight transport

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Abstract

The last decades have seen a tremendous amount of research being devoted to effectively managing vehicle fleets and minimizing empty mileage. However, in contrast to, e.g., the air transport sector, the question of how to best assign crews to vehicles, has received very little attention in the road transport sector. The vast majority of road freight transport in Europe is conducted by single drivers and team driving is often only conducted if there are special circumstances, e.g., security concerns. While it is clear that transport companies want to avoid the costs related to additional drivers, vehicles manned by a single driver sit unused whenever the driver takes a mandatory break or rest. Team drivers, on the other hand, can travel a much greater distance in the same amount of time, because mandatory breaks and rests are required less frequently. This paper investigates under which conditions trucking companies should use single or team driving to maximize their profitability. We present a novel optimization approach for simultaneously optimizing routes and crewing decisions and provide experimental evidence that, for a wide range of cost factors, operating a fleet with a mix of team and single drivers can significantly reduce operational costs when compared to typical profit margins in the sector.

Keywords Fleet management · Crewing · Vehicle routing · Scheduling

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1 Introduction

Competition in the road freight sector has led to very low profit margins close to only 3% in Europe (European Commission 2008), on average. With low profit margins, carriers are forced to make the best possible use of their trucks and truck drivers. While trucks can be used almost continuously, working hours of truck drivers in the European Union are constrained by Regulation (EC) No 561/2006. This regulation demands that truck drivers must take a 45 min break after at most $4\frac{1}{2}$ h of driving and an 11 h rest after at most 9 h of driving. Both breaks and rests may be taken in two parts of shorter duration. The rest must be taken within 24 h after the end of the previous rest period. Additional national regulations, in particular the implementations of Directive 2002/15/EC, must be complied with in each EU member state. These national regulations require that a truck driver must not work for more than 6 h without a break of at least 30 min and if the total amount of work between two rest periods exceeds 9 h, the break time must be at least 45 min. Furthermore, a driver who performs night work must not work for more than 10 h in any period of 24 h (Goudswaard et al. 2006).

Figure 1 shows a reference schedule for a single driver that can be repeated on a daily basis. This schedule comprises two $4\frac{1}{2}$ h driving periods with an intermediate break of 45 min. If the driver is not working at night, a total of $3\frac{1}{4}$ h can be used for non-driving activities on every day, as long as all necessary breaks are taken. When this pattern is repeated on a weekly basis, a weekly rest period must be taken after 5 days, so that no more than 45 driving hours are accumulated in a week. Thus, the bi-weekly driving time limit of at most 90 h is complied with.

Due to these hours of service constraints, a truck with a single driver spends less time on the road than in the parking lot. One way to increase the productivity of vehicles is to assign a team of two drivers to a truck.

If a vehicle is continuously manned by a team of two drivers, one driver can take a break while the other is driving. The minimum duration of a rest period for team drivers is reduced to 9 h and both drivers must take the rest simultaneously. The rest period must be taken within 30 h after the end of the previous rest. Figure 2 shows a

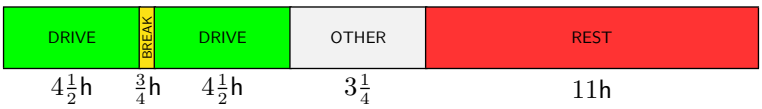


Fig. 1 Reference schedule for a single driver

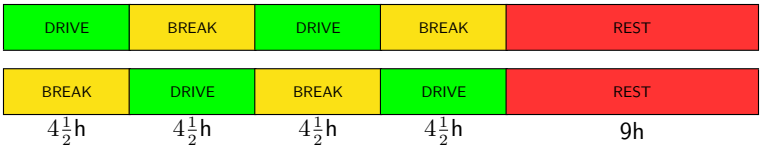


Fig. 2 Reference schedule for team drivers

reference schedule for team drivers that can be repeated until a weekly rest is taken by both drivers. In this schedule, each driver drives for $4\frac{1}{2}$ h without a break and after that, the drivers change seats. Assuming that the time required for the drivers to switch is negligible, the vehicle can keep moving without any significant break for a total of 18 h. Both drivers then take a rest period of 9 h before repeating this driving pattern.

Thus, a truck with two drivers can cover a much larger distance in a single day than a truck with a single driver. On the other hand, only one of the two drivers is actually driving while the other is unproductive. Transport companies are thus confronted with the question of whether or not to increase the productivity of the trucks at the expense of the reduced productivity of the drivers. To date, the current state-of-the-art in fleet management is lacking sophisticated methods for determining the best driver composition, and there is a strong demand for appropriate approaches that can be included in respective decision support systems.

This paper seeks to develop a better understanding of the factors influencing the decision on whether or not a team of two drivers shall be assigned to a truck. After an overview of related studies in Sects. 2 and 3 discusses the direct impact of hours of service regulations on crewing decisions based on normative driving patterns. In situations where it is reasonable to assume that truck driver schedules are mainly constrained by driving times and compulsory off-duty periods required by hours of service regulations, this normative analysis can be used to determine the best crew size depending on the total driving time. For many transport operations, operational constraints limit the applicability of normative driving patterns. In such cases, approaches for determining the best crew size must consider these operational constraints and hours of service regulations simultaneously. After providing illustrative examples highlighting that truck driver schedules can significantly differ from normative driving patterns and that different vehicle routes can be conducted with a team of two drivers than with a single driver, Sect. 4 introduces a new family of vehicle routing problems that can be used to simultaneously optimize vehicle routes, crewing decisions, and schedules. An optimization approach, based on a hybrid genetic algorithm combined with labeling techniques, is proposed. Section 5 presents an experimental analysis of selected cases to determine when a trucking company should use single or team driving. Section 6 concludes with some managerial insights from our analysis.

The main contributions of this paper are thus: (1) an analysis of crewing decision based on normative driving patterns,(2) a problem statement for a new family of combined vehicle routing, crew assignment, and scheduling problems, (3) a sophisticated hybrid genetic algorithm based on an efficient approach for quickly evaluating whether a route can be conducted by a single driver or a team of two drivers, (4) extensive computational experiments on real and artificial benchmark instances allowing to analyze the impact of different cost factors on best crew sizes, and (5) experimental evidence that, for a wide range of cost factors, operating a fleet with a mix of team and single drivers can significantly reduce operational costs compared to relying on a homogeneous crew assignment. Furthermore, we present the first approach for minimising costs for fleets where each vehicle is operated by a team

of two drivers. This approach only requires a fraction of the computational effort required for fleets where each vehicle is operated by a single driver.

2 Related work

Crewing problems in transport have been studied intensively in the airline sector (see, e.g., Kasirzadeh et al. 2017; Salazar-Gonzàlez 2014). In air transport, crews consisting of pilots and flight attendants must be assigned to scheduled flights. As in road transport, there are constraints on the crew working hours. Aviation regulations limit the flight time of pilots and impose regular rest periods. Similarly, the working hours of flight attendants are constrained by government regulations and company policies. Typical crewing problems concern the best assignment of crew members to flights in such a way that each scheduled is covered, the regulations are satisfied, and each crew member is assigned to flights forming a round trip. The number of pilots and flight attendants required for each flight is generally given and there is no benefit in assigning additional crew members to a flight. Similar problems can be found for scheduled services for other transport modes, see e.g., in Ernst et al. (2004) and Ciancio et al. (2018).

In contrast to air transport, truck drivers can interrupt a trip to take a break or rest period. Xu et al. (2003) were among the first to explicitly consider such break and rest requirements. They study a vehicle routing problem in which hours of service regulations in the United States must be complied with.

For a given vehicle route, the problem of determining a schedule for a truck driver that complies with hours of service regulations in the United States has been tackled by Archetti and Savelsbergh (2009), Goel and Kok (2012b), Goel (2014), and Rancourt et al. (2013). For European Union hours of service regulations, solution approaches have been presented by Goel (2010) and Drexl and Prescott-Gagnon (2010). Kok et al. (2011) and Goel (2012) extend these approaches by the objective of finding a feasible truck driver schedule that minimises the duration and, with thus, the respective labour costs. While above approaches focus on a single driver, Goel and Kok (2012a) present an approach for efficiently determining whether a vehicle route can be conducted by a team of two drivers.

For the combined problem of of finding vehicle routes and respective truck driver schedules complying with relevant regulations, a variety of heuristics have been presented by Zäpfel and Bögl (2008), Goel (2009), Ceselli et al. (2009), Kok et al. (2010), Prescott-Gagnon et al. (2010), and Goel and Vidal (2014). The first exact approaches for the combined vehicle routing and truck driver scheduling problem have been presented by Goel and Irnich (2017). Goel (2018) adapt this approach to consider additional regulations for driver who perform night work as well as realistic cost functions including driver wages. Tilk and Goel (2020) show how the problem can be efficiently solved using bidirectional labelling approaches. All of these approaches assume that a single driver is assigned to each vehicle throughout the planning horizon. Drexl et al. (2013) propose a heuristic algorithm for a variant of the problem where the driver to vehicle assignment can be changed dynamically.

The scientific literature considering the possibility of assigning teams of two drivers to a vehicle is scarce. Goel (2007), Bartodziej et al. (2009) and Derigs et al. (2011) consider rich vehicle routing problems in which some vehicles are operated by a single driver and some vehicles are operated by a team of two drivers. In these studies, the number of drivers assigned to a vehicle is not part of the decision problem and assumed to be given. To our knowledge, the only work studying the question of whether to assign one or two drivers to a vehicle is that by Kopfer and Buscher (2015). The authors compare the productivities of single drivers and team drivers, assuming that the workload of the drivers is organized in such a way that the main duty is driving over a longer time period. The study is based on the assumption that driving is only interrupted by breaks and rest periods required by European Union hours of service regulations. Loading and unloading times and other waiting times during which the vehicle is not moving, as well as certain important European rules on night work (see Goel 2018) are not considered.

Table 1 gives an overview over the main features of the related literature for road transport in the European Union. Check marks indicate that an aspect is explicitly considered, whereas check marks in parentheses indicate that this aspect is either implicitly or only partially considered. Previous research that considered team driving assumed that the decision of whether a single driver or a team of two drivers is assigned to a vehicle is made before routes are planned for these vehicles. So far, the decision of whether a a single driver or a team of two drivers shall be assigned to a vehicle has only be considered by Kopfer and Buscher (2015). However, their analysis does not consider important regulations on drivers who perform night work and they do not consider the problem of simultaneous routing and crewing. The rest of the literature either assumes that only single drivers are used, or that a fix share of the vehicles is assigned a team of two drivers. The only work considering crewing aspects in combination with hours of service regulations is the work of Drexl et al. (2013) who only consider the case of single drivers.

3 Crewing decisions based on normative driving patterns

This section shows how the best crew size can be determined under the assumption that truck drivers work according to normative driving patterns. This analysis differs from the analysis by Kopfer and Buscher (2015) in two ways. First, Kopfer and Buscher (2015) assumed that a reference schedule consisting of two $4\frac{1}{2}$ h driving periods with a $\frac{3}{4}$ h break in between and followed by an 11 h rest period can be repeatedly used. If such a reference schedule of $20\frac{3}{4}$ h duration was repeated multiple times, the driver would inevitably conduct night work at some day in the week. In such a case, however, the working time within any period of 24 h must not exceed 10 h. Thus, the assumption of Kopfer and Buscher (2015) can not be made. Therefore, we use the reference schedules shown in Figs. 1 and 2. Second, Kopfer and Buscher (2015) used representative cost values for driver wages and truck rental, whereas our analysis finds simple conditions that can be used by transport managers to determine whether to use a single driver or a team of two drivers depending on the specific cost structure of their company.

Table 1 Overview over related work on European hours of service regulations

Paper	Regulations		Drivers		Costs			Problem	
	EC561	Night work	Single	Team	Mileage	Vehicles	Labour	Routing	Crewing
Goel (2007)	✓		✓	✓	✓			✓	
Zäpfel and Bögl (2008)	(✓)		✓		✓	✓	✓	✓	
Ceselli et al. (2009)	(✓)		✓		✓	(✓)	(✓)	✓	
Goel (2009)	✓		✓		✓	✓		✓	
Bartodziej et al. (2009)	(✓)		✓	✓	(✓)	(✓)	(✓)	(✓)	
Goel (2010)	✓		✓						
Drexl and Prescott-Gagnon (2010)	✓		✓		✓				
Kok et al. (2010)	✓		✓		✓	✓		✓	
Prescott-Gagnon et al. (2010)	✓		✓		✓	✓		✓	
Derigs et al. (2011)	✓		✓	✓	✓	✓	✓	✓	
Kok et al. (2011)	✓		✓			✓			
Goel (2012)	✓		✓			✓			
Drexl et al. (2013)	✓		✓		✓	✓	✓	✓	✓
Goel and Kok (2012a)	✓			✓					
Goel and Vidal (2014)	✓		✓		✓	✓	✓	✓	
Kopfer and Buscher (2015)	✓		✓	✓	✓	✓	✓		
Goel and Irnich (2017)	✓		✓		✓	✓		✓	
Goel (2018)	✓	✓	✓		✓	✓	✓	✓	
Tilk and Goel (2020)	✓	✓	✓		✓	✓	✓	✓	
This study	✓	✓	✓	✓	✓	✓	✓	✓	✓

The travel time required for the same travel distance can differ significantly if drivers operate according to the reference schedules shown Figs. 1 and 2. The resulting time required for single and team drivers for a driving time of up to 90 h, i.e., the bi-weekly driving limit for a single driver is shown in Fig. 3. The gray line illustrates the duration required by a single driver. After five daily driving periods, a single driver reaches the maximum average amount of 45 h driving per week.

The black line illustrates the duration required by a team of two drivers. We again assume that the drivers repeat the same pattern in the subsequent week. Therefore, a weekly rest period of 45 h must be scheduled before the start of the next week and at most $168 - 45 = 123$ h are available for driving and daily rest periods. Within this time frame, team drivers can have four cycles of 18 h of driving followed by a rest of 9 h and another driving period of 15 h. Thus, team drivers can drive up to 87 h per week.

In this comparison, it must be noted that a single driver has $3\frac{1}{4}$ h daily that can be used for loading or unloading or other non-driving activities, whereas such activities reduce the amount of driving time that team drivers can conduct within the week.

Depending on the cost structure of the carrier, the question of whether to use a single driver or team drivers may be answered differently. Assuming a daily cost of c^{truck} for the vehicle and c^{driver} for each driver, the time-related cost of operating a vehicle for d^{single} days with a single driver is

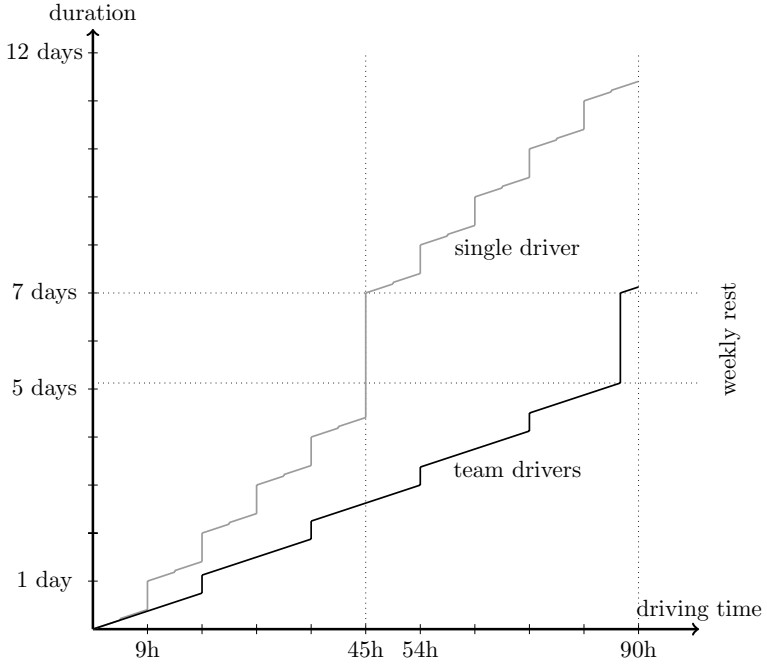


Fig. 3 Durations required for single and team drivers

$$(c^{\text{truck}} + c^{\text{driver}}) \cdot d^{\text{single}},$$

and the cost of operating a vehicle for d^{team} days with a team of two drivers is

$$(c^{\text{truck}} + 2c^{\text{driver}}) \cdot d^{\text{team}}.$$

Obviously, a single driver is less costly if team driving does not reduce the number of days required to perform a trip, i.e., if $d^{\text{single}} = d^{\text{team}}$. If team driving, however, requires only half of the number of days required by a single driver or less, i.e., if $d^{\text{single}} \geq 2d^{\text{team}}$, then team driving is less costly.

For $d^{\text{team}} < d^{\text{single}} < 2d^{\text{team}}$, the costs for a single driver are the same as the costs for a team of two drivers if

$$\frac{c^{\text{driver}}}{c^{\text{truck}}} = \frac{d^{\text{single}} - d^{\text{team}}}{2d^{\text{team}} - d^{\text{single}}}.$$

For larger values of $c^{\text{driver}}/c^{\text{truck}}$, the costs for a single driver are smaller, and for smaller values, the costs for team drivers are smaller. Table 2 shows the number of days required for single and team drivers depending on the driving time (in hours) and the resulting best crew size.

For longer routes, team driving is the cheaper alternative for most ranges. For driving times between 18 and 27 h, a single driver is cheaper if $c^{\text{driver}} > c^{\text{truck}}$, i.e., if the daily cost for the driver is larger than the daily cost of the vehicle. For driving times between 36 and 45 h and between 87 and 90 h, a single driver is cheaper if $c^{\text{driver}} > 2c^{\text{truck}}$, i.e. if the daily cost for the driver is larger than two times the daily cost for the vehicle.

Table 2 Comparison of single and team drivers for trips with different driving times

Driving time	d^{single}	d^{team}	Best crew size
(0,9]	1	1	1
(9,18]	2	1	2
(18,27]	3	2	1 or 2
(27,36]	4	2	2
(36,45]	5	3	1 or 2
(45,54]	6	3	2
(54,63]	7	3	2
(63,72]	8	4	2
(72,81]	9	4	2
(81,87]	10	5	2
(87,90]	10	6	1 or 2

4 Crewing decisions based on operational models

In the above section, we assumed that the only duty of truck drivers is to drive, and that there are no other activities (e.g., such as loading or unloading) or operational constraints. Under these assumptions, drivers can follow the reference schedules shown in Figs. 1 and 2, where the only factors influencing the decision on team driving are the driving time and the ratio between daily driver wages and vehicle costs. In most transport operations, however, these assumptions are too simplistic because operational requirements concerning business hours of customers, vehicle capacities, and service durations, among others, can have a significant impact on truck driver schedules.

Figures 4 and 5 give examples of schedules for single and team drivers visiting different customers subject to various operational constraints. These examples were obtained from the experiments described later in this paper. In these experiments, customers must be visited within given time windows, stationary work for loading or unloading the vehicle is required at each customer, and the selection of customers that can be visited in the same route is constrained by capacity limitations. These schedules differ significantly from the reference schedules of Figs. 1 and 2 and the assignment of one or two drivers is not a free choice. In particular, if the route corresponding to the schedule shown in Fig. 5 was to be executed by a single driver, the mandatory breaks and rest periods would cause substantial delays, leading to violations of time-window constraints.

To better understand the impact of operational constraints on crewing decisions, consider an example where a transport company has to deliver two half truckloads to two customers who are $4\frac{1}{2}$ h of driving away from the depot and where the driving distance between the customers is 2 h. To fulfil both customer requests and allow the drivers to return to the depot on the same day, two trucks are required if each truck is operated by one driver, whereas a single truck suffices for team driving. Figure 6 illustrates this example. In both cases, two daily salaries must be paid. Because team driving only requires one vehicle for a total of 11 h, instead of two vehicles for a total of 18 h, team driving can reduce both cost and distance.

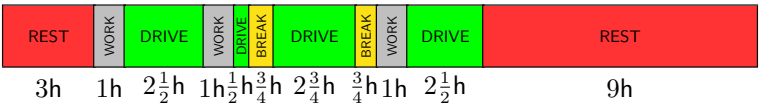


Fig. 4 Example schedule for a single driver

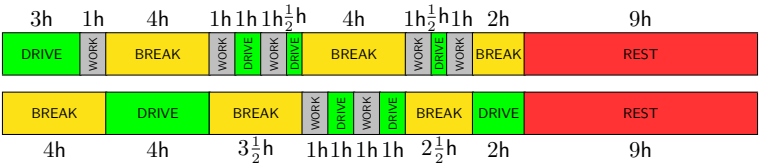


Fig. 5 Example schedule for team drivers

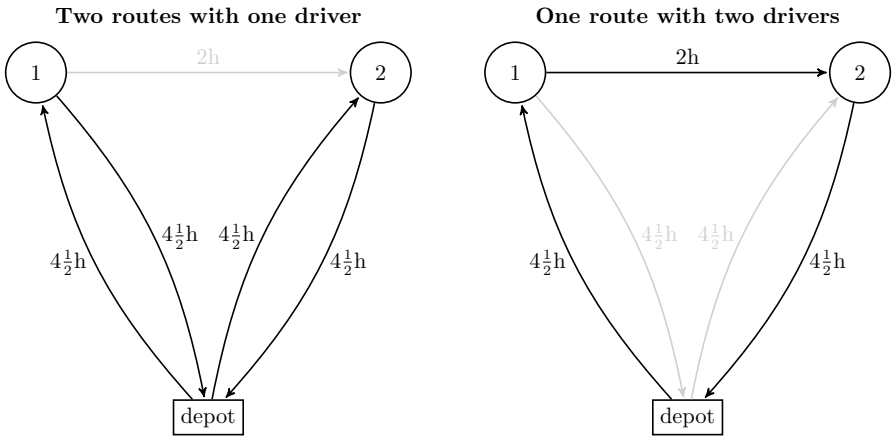


Fig. 6 Team driving can reduce both cost and distance

As the above examples show, operational constraints can influence routing decisions, truck driver schedules, and with them, the choice of using single or team drivers. A classification of operational requirements in terms of type of carrier and goods, geographic distribution of customers, distances, service times, time-window tightness, transport volumes and capacities, etc. does not help much in determining the best crew compositions for the different classes, because the effects of these factors on crew size are highly interrelated and of combinatorial nature. For example, geographic proximity of customers and tight time-windows may be a reason to use single drivers if the time-window tightness results in large waiting times when visiting the customers within the same route. On the other hand, geographic proximity of customers and tight time-windows may also be a reason to use team drivers, because a single driver might not be able to visit the customers within the same route due to the additional time required for mandatory breaks and rests. Similar effects can be found for other classification schemes.

4.1 Problem formulation

In order to adequately consider these interrelated effects, we propose to tackle the team driving question by solving combinatorial optimization problems considering typical operational requirements. For this purpose, we present a new family of vehicle routing problems for assigning drivers to vehicles and optimizing routes and schedules. These problems can be generally represented by the following optimization model:

$$\begin{aligned} \text{minimize} \sum_{r \in R_1} (c^{\text{truck}} d_r + c^{\text{driver}} d_r + c^{\text{distance}} k_r) x_r \\ + \sum_{r \in R_2} (c^{\text{truck}} d_r + 2c^{\text{driver}} d_r + c^{\text{distance}} k_r) x_r \end{aligned} \tag{1}$$

$$\text{subject to} \sum_{r \in R_1 \cup R_2} a_{ir} x_r = 1 \quad \forall i \in V \tag{2}$$

$$x_r \in \{0, 1\} \quad \forall r \in R_1 \cup R_2, \tag{3}$$

where V represents a set of customers that must be visited by exactly one route, R_1 represents the set of all feasible routes that can be operated by a single driver, R_2 represents the set of all feasible routes that can be operated by a team of two drivers, and a_{ir} is a binary parameter set to 1 if and only if customer $i \in V$ is visited by route $r \in R_1 \cup R_2$.

Observe that the complexity inherent to the routing decisions is fully captured within the definition of the sets R_1 and R_2 representing all the possible feasible routes and their costs. However, these sets cannot be enumerated in practice, as they contain a number of routes which grows exponentially with the problem size (as represented by the number of deliveries). As a consequence, sophisticated search approaches that jointly find good candidate routes and optimize crewing decisions must be designed. In the following, we will build upon a decade of methodological studies to propose a practical solution approach.

In this model, we assume that $R_1 \cap R_2 = \varnothing$ for modeling simplicity, i.e., we distinguish single-driver and team-driving routes (even with the same sequence of customers) since they have different costs. This can easily be achieved, for example, by using dedicated starting nodes for single and team drivers. For each route $r \in R_1 \cup R_2$, the parameters d_r and k_r denote the number of days required and the total distance (in kilometers) traveled, and c^{truck}, c^{driver}, and c^{distance} denote the daily cost for a truck, the daily cost for a driver, and the cost per kilometer. Each binary decision variable x_r is set to 1 if and only if route $r \in R_1 \cup R_2$ is selected in the solution. Objective (1) seeks to minimize the total cost of all the routes, and Constraint (2) ensures that each customer is visited by exactly one route.

This formulation permits to model the impact of cost factors on the decisions of visiting customers using single or team driver routes. We assume, in the scope of the present study, that the salary of a team of drivers for each day of operations is twice that of a single driver. If needed, the model could be adapted to accommodate other cost definitions. Moreover, the operational requirements imposed on individual routes (e.g., capacity constraints, pickups and deliveries, loading constraints, maximum route lengths) are fully captured within the definition of the sets R_1 and R_2. Thus, the formulation models a large variety of vehicle routing problems. We will focus our presentation on the operational constraints of the well-known *vehicle routing problem with time-windows (VRPTW)* (see, e.g., Bräysy and Gendreau 2005a, b), which aims at finding a minimal cost set of routes for a fleet of vehicles such that a given set of customers is visited within given time-windows and vehicle capacities are not exceeded. The sets R_1 and R_2 therefore include all routes satisfying the constraints of the VRPTW and hours of service regulations for single or team drivers. Whether a route complies with hours of service regulations can be validated by solving a so-called *truck driver scheduling problem*, i.e., the problem of determining a schedule for a given route such that all customers in the route are

visited within given time windows and that applicable hours of service regulations are complied with. It must be noted, that despite of limiting our presentation to this particular problem variant, other operational constraints on the feasibility of routes can be tackled by adequately adapting the approach described in the next sections.

4.2 Solution framework

As the sets of feasible routes for single drivers and team drivers (R_1 and R_2) are usually too large to enumerate, the combined vehicle routing, crew assignment and scheduling problem cannot be easily solved. Goel (2018) presented an exact branch-and-price approach for the case where only single drivers are considered. Although it is possible to adopt this approach to simultaneously consider single and team drivers, finding exact solutions would require unpredictably long computational runs for problems of practical relevance. Furthermore, the large computational effort would make it impractical to run extensive computational experiments to measure the impact of different cost factors on the best crew size.

Therefore, we show how local search-based metaheuristics developed for the single driver case can be adapted to the case of simultaneous routing and crew optimization. For the purpose of this paper we opted to adapt the hybrid genetic search (HGS) of Goel and Vidal (2014) to obtain solutions of consistently high quality in a controlled time. HGS is based on the iterative generation of new solutions via a problem-tailored crossover and efficient local-improvement techniques, in combination with population-diversity management strategies that promote the exploration of a wide variety of solutions. Figure 7 provides an overview of the main steps of the algorithm. It uses the same general-purpose operators as the unified hybrid genetic search (UHGS—Vidal et al. 2014), which has been established as the most successful method for over fifty VRP variants, retrieving almost systematically the optimal solutions which are available for these problems. The main adaptations of

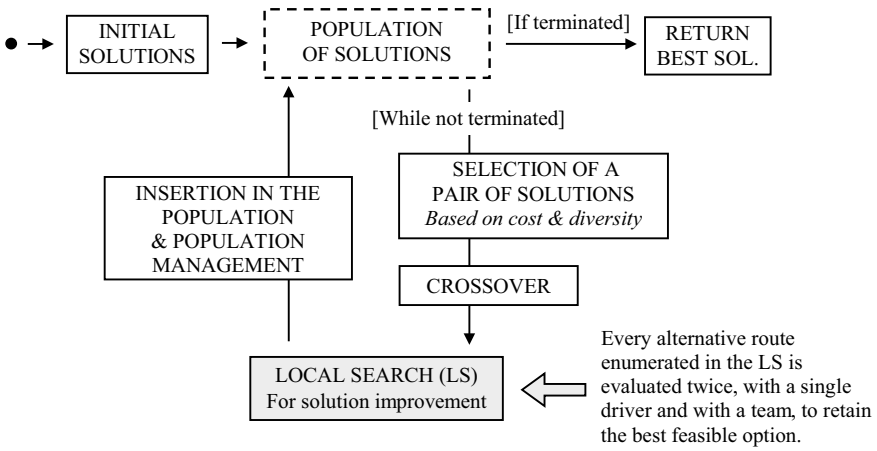


Fig. 7 General principles of HGS

the HGS for our problem reside in the local search phase, in which it becomes necessary to determine whether a modified route can be operated by a single driver or a team of two drivers. Similarly, if other local-search based solution frameworks are used, the main adaptations required would be to evaluate the cost of any route after a change, i.e., after a move in the local search. Thus, fast route-evaluation algorithms are needed that are capable of considering the particular characteristics of the problem at hand, in our case, the VRPTW.

4.3 Route evaluation algorithms

For every route $r = (n_1, n_2, \ldots, n_k)$ explored during the local search, the algorithm must determine whether there is a feasible schedule for a single driver or a team of two drivers and the necessary number of days in both cases. This is done with a labeling algorithm, which begins with a label representing the state of the driver(s) at the start of the route. We assume that all drivers are fully rested at the start of the route. Then, this label is iteratively updated using appropriate resource extension functions (REFs) associated to arcs of an auxiliary network similar to the one shown in Fig. 8. The REFs $f^{\text{trip}}_{n_i n_j}$and REFs $f^{\text{visit}}_{n_i}$ are used to initialize the total amount of driving required from node n_i to node n_j and to update the label corresponding to a state after visiting location n_i within the corresponding time-window. The REFs $f^{\text{drive}}_{\Delta}$ are used to update the label corresponding to a state after driving for a duration of Δ. The REFs $f^{\text{offduty}|i}_{\Delta}$ are used to update the label corresponding to a state after an off-duty period of type i for a duration of Δ.

For single drivers, our algorithm uses the labelling approach by Goel (2018) to determine truck driver schedules with minimal duration. This approach uses resource labels indicating the time, the number of days en-route, the cumulative driving time since the last break, the cumulative driving time since the last rest, the cumulative working time since the last break, the time elapsed since the last rest period, the offduty time required to complete a break, the offduty time required to complete a rest, and the latest possible completion time of the last rest in the case the duration of the rest period is extended. The regulations for single driver require four different types of REFs $f^{\text{offduty}|i}_{\Delta}$, where i indicates the first part of a break, the last part of a break, the first part of a rest, or the last part of a rest.

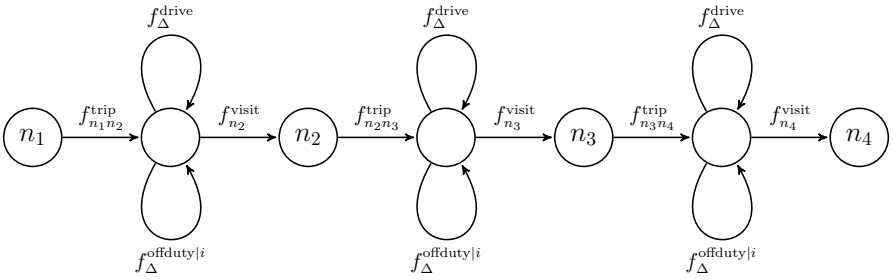


Fig. 8 Network and REFs used for checking feasibility of a route $r = (n_1, \ldots, n_4)$

For team drivers, we extend the labelling approach of Goel and Kok (2012a) which does not consider the constraints on the cumulative working time for drivers conducting night work. Furthermore, the approach of Goel and Kok (2012a) only focuses on feasibility and can not be used to find schedules minimising the number of working days. In our labelling approach, we use labels indicating the current time, the start time, the latest possible start time, the cumulative driving time since the last rest, the cumulative working time since the last rest, the time elapsed since the last rest period, and the latest possible completion time of the last rest in the case the duration of the rest period is extended. Only one REF $f_{\Delta}^{\text{offduty}|i}$ is required where i indicates a rest taken by both drivers simultaneously. The breaks required by each driver are assumed to be taken when the other driver is driving and the time required for drivers to switch seats is considered to be negligible. A detailed description of the truck driver scheduling approach for team drivers is given in "Appendix A".

As determining a truck driver schedule for team drivers can be done with only one REF of type $f_{\Delta}^{\text{offduty}|i}$, the number of alternatives to be considered is much smaller than for the single driver case in which four different REFs of type $f_{\Delta}^{\text{offduty}|i}$ are required. This makes our route evaluation approach for team drivers significantly faster than the approach for single drivers.

4.4 Speed-up strategies

During a typical run of a metaheuristic solution approach, millions of local search moves must be evaluated and each move evaluation implies new route evaluations for single and team drivers. To reduce the computational overhead of route evaluations, we first check whether a feasible team driver schedule exists, because otherwise, there cannot be a feasible single driver schedule for the route. Furthermore, determining whether a route can be conducted by a single driver takes about 20 times longer than determining whether it can be conducted by a team of two drivers. Only if a feasible team driver schedule is found, a route evaluation for a single drivers is required.

A variety of techniques is used to speed-up the remaining route evaluations. To avoid evaluating unnecessarily many moves, we use memories with constant-time hash calculations to store route evaluations, as well as static neighborhood restrictions (Goel and Vidal 2014). Furthermore, we exploit *lower bounds* on move evaluations, as in Vidal (2017), to quickly filter any move that has no chance of contributing to a better solution. We observe that the duration for a team of two drivers is a lower bound on the duration for a single driver. Therefore, we calculate upper bounds on the savings of a local search move, by computing the optimized duration as if a team was driving, but with the cost coefficient for a single driver. A local search move with a negative upper bound on the savings cannot improve the incumbent solution.

In order to assess the effect of these speed-up techniques we conducted computational experiments on a set of benchmark instances from the literature. Detailed results of these experiments can be found in Appendix B. Our experiments show that the use of memory structures leads to a speed-up by a factor of 4.03 and the

use of the lower bounds on move evaluations accelerating the search by a factor of 2.94 on average. With our lower bounds we were able to filter 90% of the moves on average, considerably reducing the number of calls to the time-consuming single-driver schedule optimization routine. Combining both speed-up techniques leads to an overall speed-up by a factor of 18.24 and allows to quickly find high-quality solutions for the combined problem of assigning drivers to vehicles and optimizing routes and schedules subject to respective hours of service regulations.

5 Experimental analysis

To understand under which conditions a trucking company should use single and team driving, we conducted experiments based on instances derived from the planning problem of one of ORTEC's retail customers in Eastern Europe. This retailer is using ORTEC's route optimization engines to construct routes by doing batch optimization runs for three days ahead. So far, the customer is executing all routes with single drivers. Most of the routes are single-day trips, and others are longer multi-day trips.

The instances are grouped in three datasets, each corresponding to a separate DC. Figure 9 illustrates the geographical spread of the addresses in each dataset. For each dataset, we created five instances based on the locations shown in the figure, each time randomly removing 20% of the original addresses to create variability in the customer locations. The planning horizon includes three days (Monday till Wednesday), and time-window lengths range from 3 to 16 h, with an average of 9 h. The original planning problem involves a heterogeneous fleet with small differences in vehicle capacity. To simplify the experimental setting and to focus on the crew size aspects, we assume a homogeneous vehicle fleet with a vehicle capacity set to the largest vehicle type in the original problem. The numbers of customers in each dataset are 60, 70, and 88, respectively. The vehicle capacity is 18 pallets and the average number of pallets demanded by the customers is 7.7 pallets, leading to an average of 2 to 3 stops per trip. The variation in customer demand leads to a mix of short and long routes with one to seven stops per route. The distribution of the customer locations is shown in Fig. 9. Each

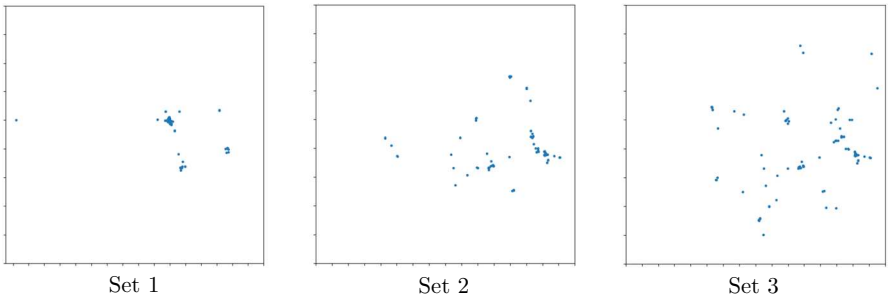


Fig. 9 Customer distribution of real-life instances

region shows an area of roughly 1000 times 1000 km with a depot located close to the centre. Due to confidentiality reasons the exact region and scale as well as the location of the central depot can not be revealed. Driving distances and durations are based on shortest path distances in the road network and obtained from a geographic information system.

We used the proposed HGS to solve these instances and determine the least cost routes for the cases where (1) all vehicles are allocated a single driver, (2) all vehicles are allocated a team of two drivers, and (3) the decision on whether to assign one or two drivers to a vehicle is part of the optimization. To avoid random bias, we ran the heuristic algorithm five times on each instance with different seeds.

Based on cost estimates provided by ORTEC, we use the following baseline cost values: labor costs of €100 per driver per day (see Comité National Routier 2016), truck costs of €100 per day (i.e., leasing or amortized acquisition costs, but excluding fuel costs), and distance-related costs of €0.25 per km (i.e., fuel, wear and tear, and possible tolls). We also assume, for now, that the time required for loading and unloading the vehicle is independent of the number of drivers assigned to the truck.

Table 3 shows average results of our experiments for single drivers, team drivers, and an optimized driver assignment. For each set of instances, the table shows the average crew size, the average costs as a percentage of the cost of an optimized crew assignment, the average number of days required per tour, and the average computation time (CPU) as a percentage of the effort required for the single driver case. The average crew size is calculated as $(1 \cdot k_1 + 2 \cdot k_2)/(k_1 + k_2)$ where k_1 and k_2 are the number of single driver and team driver routes. An average crew size of 1 indicates that all routes are conducted by single drivers, an average crew size of 2 indicates that all routes are conducted by team drivers, and an average crew size of 1.5 would indicate that half of the routes are operated by single driver and the other half by team drivers.

Table 3 Impact of crew-size decisions on real-world instances

	Only Single	Only Team	Optimized
Set 1			
Avg. crew size	1	2	1.035
Avg. cost	100.8%	138.2%	100%
Avg. days	1.032	1	1.003
Avg. CPU	100%	40.7%	102.7%
Set 2			
Avg. crew size	1	2	1.127
Avg. cost	103.2%	124.9%	100%
Avg. days	1.111	1	1.007
Avg. CPU	100%	39.42%	106.5%
Set 3			
Avg. crew size	1	2	1.125
Avg. cost	103.5%	123.9%	100%
Avg. days	1.114	1	1.001
Avg. CPU	100%	57.55%	104.1%

Relying exclusively on team drivers is clearly not cost-efficient for these instances. Nevertheless, relying exclusively on single drivers is also not advisable and operational costs can be reduced by between 0.8% and 3.5% on average by assigning team drivers to 3% to 13% of the routes. Considering the low profit margins of around 3% in European road freight transport (European Commission 2008), these savings are remarkable. Thanks to our acceleration techniques, the computational effort required for simultaneous routing and crew optimization is only marginally higher than for routing with a fixed assignment of one driver to each vehicle.

Table 4 shows the total number of routes, the total number of days a truck is required and the total number of daily salaries to be paid. These results are averaged over the five runs of our algorithm. As observed in these experiments, optimizing the crew size eliminates most of the multi-day tours such that the vast majority of the routes in the solutions require only one day. As each route is evaluated for single and team drivers, we know that for any team driver route in the solution, it is impossible for a single driver to execute the same route within a day without violating time windows. Otherwise, a solution with fewer drivers and lower costs would have been found. Overall, the number of days on which a truck is required is significantly reduced by optimizing crew decisions and using teams for a few selected routes. The use of teams increases the total amount of salaries paid to drivers, but this increase is relatively small in comparison to the reduction of truck costs. When operating exclusively with team drivers, all of the routes require only one day.

We repeated our experiments with different cost parameters and under the hypothesis that the service time at the customer locations can be reduced (by 50 or 25%) if two drivers are available for loading and unloading the vehicle. However, the best crew sizes did not vary much from those reported in Table 3. These experimental results are well aligned with our analysis of normative driving patterns for single and team drivers presented in Sect. 3. The insensitivity to the cost parameters is not surprising given the short lengths of the routes.

In general, it can be assumed that transport companies seek to obtain a pool of transportation requests that fit particularly well to the company's way of conducting business. Instead of fulfilling a transportation request that does not suit current practice, a transport company may either decide to reject the request or to renegotiate some of the requirements. In other words, if a transport company is operating all vehicles with a single driver, it will seek to obtain transportation requests that can be combined into cost-efficient single-driver routes, and the company will try

Table 4 Solution characteristics for real-world instances

	Only Single	Only Team	Optimized
Number of routes	505.8	496	501.2
Number of single driver routes	505.8	–	449.8
Number of team driver routes	–	496	51.4
Number of days a truck is required	552.6	496	502.8
Number of daily salaries	552.6	992	554.2

to renegotiate, e.g., time constraints on deliveries to certain locations to achieve better delivery consolidation. When generating instances based on data of companies operating all vehicles with single drivers, as we did for our above experiments, it is likely that these effects create an inherent bias toward single driver routes in optimized crew compositions. To eliminate this bias and consider a more diverse set of scenarios, we conduct additional experiments on artificial benchmark instances commonly used to evaluate the performance of optimization approaches for vehicle routing problems with time-windows. The 56 instances used in these experiments were introduced by Solomon (1987) and adapted by Goel (2009) and Goel (2018) for combined vehicle routing and truck driver scheduling problems in the European Union. The instances can be grouped into three classes, R, C, RC, containing randomly-distributed, clustered and mixed customer locations, respectively. Each instance contains 100 customers, and the average size of the time-windows per instance ranges from less than 7 h to over 107 h. The planning horizon is 144 h (6 days) and the maximum driving time (without compulsory breaks and rests) between two customers is approximately one day. Table 5 shows the results of our experiments using the same baseline cost values as for the real-world instances.

Under these assumptions, operating each vehicle with two drivers is more cost-efficient than using only single drivers, but the best results are again obtained with an optimized crew composition. Compared to only using single drivers, optimized crew assignments can reduce operational costs by between 5.6 and 7.2% on average. The cost benefit compared to exclusively relying on team drivers is between 2.8 and 5.0% on average. The average tour durations are higher than in the real-world instances, indicating that the driving time in some routes falls into the range where, according to Table 2, the best crew size depends on the cost structure. For these sets of instances, the additional computational effort for simultaneous routing and crew optimization is larger than for the real-world instances. However, considering that

Table 5 Impact of crew-size decisions on artificial instances

	Only single	Only Team	Optimized
R			
Avg. crew size	1	2	1.731
Avg. cost	107.0%	102.8%	100%
Avg. days	2.365	1.477	1.507
Avg. CPU	100%	58.1%	142.0%
C			
Avg. crew size	1	2	1.475
Avg. cost	107.2%	105.0%	100%
Avg. days	2.892	2.762	2.406
Avg. CPU	100%	90.4%	121.7%
RC			
Avg. crew size	1	2	1.670
Avg. cost	105.6%	103.0%	100%
Avg. days	2.480	1.578	1.667
Avg. CPU	100%	59.7%	161.3%

each route has to be evaluated for a single driver and for team drivers, the computational overhead for simultaneous routing and crew optimization is clearly justified considering the significant cost savings.

Table 6 shows the total number of routes, the total number of days a truck is required and the total number of daily salaries to be paid over all instances. Interestingly, the overall number of routes is higher when optimizing the crew size. As team drivers help reducing the duration required for these routes, the number of days a truck is required is significantly reduced without excessively increasing the daily salaries to be paid.

We conducted extensive additional experiments with different cost parameters to avoid any possible bias. In particular, we varied the ratio of the daily driver to the truck cost and the ratio of the cost per kilometer to the daily truck cost. A factorial design with all 25 possible combinations of parameters $(\frac{c^{\text{driver}}}{c^{\text{truck}}}, \frac{c^{\text{distance}}}{c^{\text{truck}}}) \in \{0.25, 0.5, 1, 2, 4\} \times \{\frac{1}{100}, \frac{1}{200}, \frac{1}{400}, \frac{1}{800}, \frac{1}{1600}\}$ was used. Thus, the daily driver costs range between a quarter and 4 times the daily costs for the vehicle, and the daily truck costs range between the costs for 100 to 1600 km of traveled distance. Furthermore, we made various assumptions about the service durations at customer locations. More precisely, we consider three different settings, in which the service duration of team drivers (denoted s^{team}) is 50%, 75%, or 100% of the service duration of a single driver (denoted s^{single}). For each of the 25 cost-parameter configurations and the three assumptions on service durations for team drivers, we ran the algorithm five times on each of the 56 instances with different random seeds and report average solution values over these runs. Furthermore, we repeated the experiments under the assumptions that all vehicles are operated by a single driver and all vehicles are operated by two drivers.

The box-and-whisker plots in Figs. 10, 11 and 12 show the average number of drivers per vehicle in the solutions obtained for different cost parameters and assumptions on service durations. Figures 10a, 11 and 12a show how a change in labor costs impacts the best crew size for fix values of $c^{\text{distance}} = 0.25$ and $c^{\text{truck}} = 100$ (i.e., $\frac{c^{\text{distance}}}{c^{\text{truck}}} = \frac{1}{400}$), and Figs. 10b, 11 and 12b show how a change in mileage costs impacts the best crew size for fix value of $c^{\text{driver}} = c^{\text{truck}} = 100$ (i.e., $\frac{c^{\text{driver}}}{c^{\text{truck}}} = 1$).

The figures clearly show that the share of team drivers grows with a decrease of driver wages. Not surprisingly, with $s^{\text{team}} = 0.5 \cdot s^{\text{single}}$ the possibility of reducing the service time required at the customers makes team driving particularly beneficial. The highest sensitivity to a change in driver wages can be observed for $s^{\text{team}} = s^{\text{single}}$.

Table 6 Solution characteristics for artificial instances

	Only single	Only team	Optimized
Number of routes	614.4	593.6	635
Number of single driver routes	614.4	–	231.6
Number of team driver routes	–	593.6	403.4
Number of days a truck is required	1552.2	980.6	1108.8
Number of daily salaries	1552.2	1961.2	1673.6

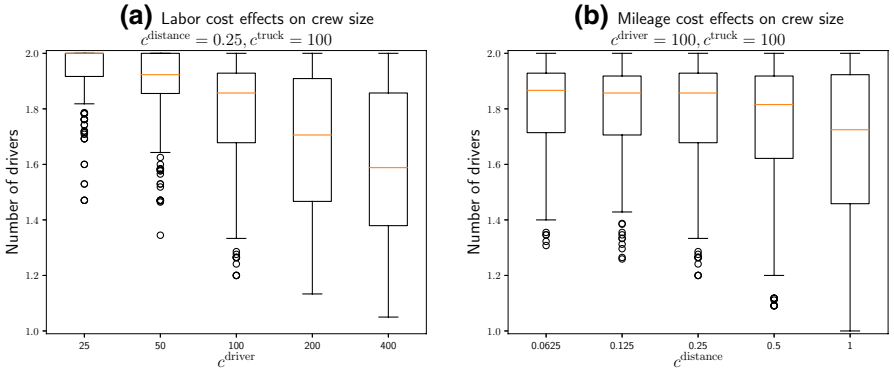


Fig. 10 Number of drivers for modified Solomon instances for $s^{\text{team}} = 0.5 \cdot s^{\text{single}}$

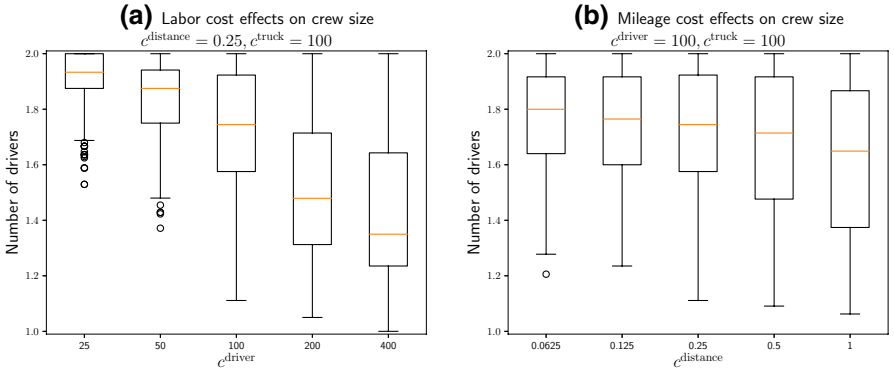


Fig. 11 Number of drivers for modified Solomon instances for $s^{\text{team}} = 0.75 \cdot s^{\text{single}}$

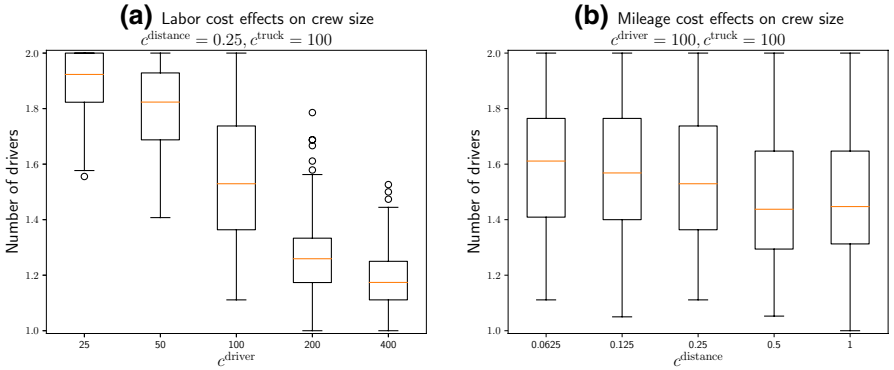


Fig. 12 Number of drivers for modified Solomon instances for $s^{\text{team}} = s^{\text{single}}$

Even with extremely high driver wages, a significant share of team drivers is used. This is particularly interesting, because it indicates that team driving is also beneficial in high-income countries.

The effect of mileage costs is less pronounced but still notable, and we can see that higher mileage costs result in a reduced share of team drivers. As expected, we observe that the traveled distance decreases with higher mileage costs. Although the number of routes also decreases, the number of daily driver shifts is increased. This indicates that schedules include more waiting times resulting from time-window constraints at customer locations. It appears that the labor costs related to these waiting times outweigh the potential benefits of reducing mileage by using team drivers, and therefore, their share decreases.

The same effects can also be observed for different values of the constant parameters used in Figs. 10, 11 and 12. "Appendix C" provides average results for the full factorial design. It must be noted that for all values of the cost parameters and the different assumptions on service durations, an average of at least 12.7% of all vehicles are operated by two drivers and an average of at least 7.0% of all vehicles are operated by one driver. This shows that independently of the cost parameters and assumptions on service durations, the best policy overall is to have a mixed composition of single and team drivers.

Figures 13, 14 and 15 show the relative cost increase of single and team driving compared to an optimized crew assignment assuming fixed values of $c^{\text{distance}} = 0.25$ and $c^{\text{truck}} = 100$. Using only single drivers can be substantially more expensive than using a mix of single and team drivers, particularly for low and medium driver wages. If team drivers can parallelize service tasks at customer locations costs savings are substantial, even with high driver wages. Conversely, using only team drivers can be considerably more expensive than using a mix of single and team drivers for high driver wages. Overall, cost savings of 10% and more can be achieved for many instances and some outliers indicate that a pure strategy of using only single or only team drivers can have a disastrous effect on efficiency compared to a mixed strategy. Again the same effects can also be seen for different values of the constant

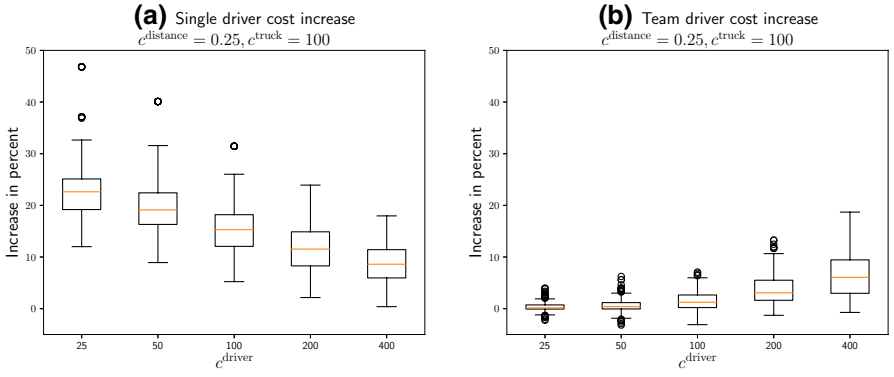


Fig. 13 Cost difference for modified Solomon instances for $s^{\text{team}} = 0.5 \cdot s^{\text{single}}$

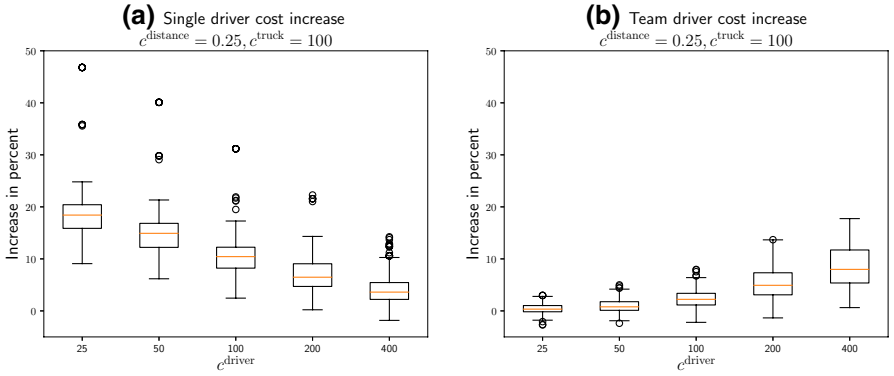


Fig. 14 Cost difference for modified Solomon instances for $s^{\text{team}} = 0.75 \cdot s^{\text{single}}$

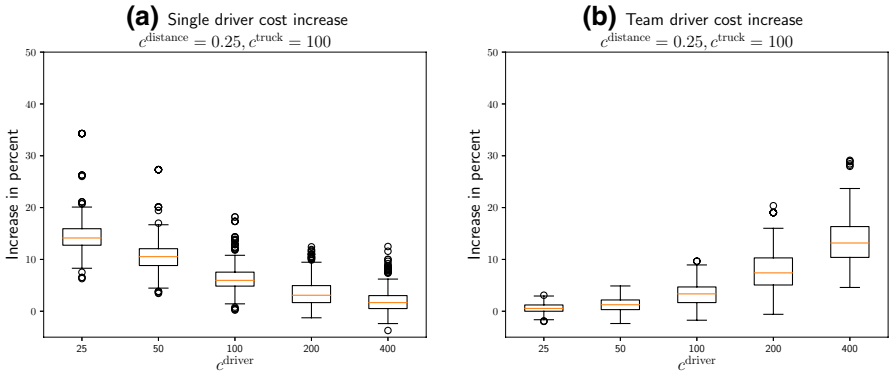


Fig. 15 Cost difference for modified Solomon instances for $s^{\text{team}} = s^{\text{single}}$

parameters used in Figs. 13 to 15 and average results for the full factorial design are provided in "Appendix C"

Averaged over all Solomon instances and all scenarios, the computational effort required for simultaneous routing and crew optimization is only 27% higher than the effort required for solving the vehicle routing and truck driver scheduling problem with single drivers.

We finally investigated potential other factors having an effect on crew size, such as distances, demands, time window tightness, and combinations thereof. However, we could not find clear correlations involving these factors that would hold across all scenarios. Apparently, the combinatorial nature of vehicle routing under hours of service regulations can cause large changes in solutions even with small changes in the input data. On the other side, large changes, for example, with respect to the tightness of time windows may not have any effect on the optimal solution if the time windows still include the scheduled times in the optimal solution. Moreover, factors that can have a direct impact on the best crew size for any particular route, e.g. the distance between customers, may have a negligible

effect on the best crew size if the routes are the outcome of the optimization process. In order to allow the reader to further analyze our results and test additional hypotheses, we provide all our experimental results at https://doi.org/10.7910/DVN/KCIGSU.

6 Managerial insights and conclusions

In this paper, we have evaluated under which conditions trucks should be manned by a single driver or a team of two drivers. For cases where driver schedules can be based on normative driving patterns, Table 2 can be used to determine the best crew size depending on the driving time and the ratio of daily labor costs and daily vehicle costs. Our analysis of normative driving patterns shows that team driving is particularly beneficial for long routes for which route durations can be reduced when using a team of two drivers.

Whenever there are operational constraints that have an impact on routes and schedules, crewing decisions cannot be solely based on normative driving patterns. To analyze crewing decisions in such cases, we presented a new family of vehicle routing problems for the simultaneous optimization of driver assignments, routes, and schedules. We presented a solution approach based on an hybrid genetic search framework that has proven to be extremely flexible with regards to the different operational characteristics. In our approach, we use problem specific route evaluations to determine whether a route shall be conducted by a single driver or team drivers. We proposed an efficient approach for quickly evaluating neighborhood moves using lower bounds that help to filter out on average 90% of the time-consuming single-driver route evaluations, thus leading to an effective solution procedure. Overall, our solution approach, involving the decision whether to assign one or two drivers to a vehicle, requires only moderate additional computational effort compared to the case where all vehicles are assumed to be assigned a single driver only. For the real-life instances, running times increased by only 1% on average and, for the artificial instances, running times increased by 27% on average.

We tested our approach on instances derived from real cases and a collection of artificial instances covering a range of alternative characteristics. Our experiments with a wide range of cost factors and scenarios, show how many drivers should be assigned to the vehicles and how much can be saved in comparison with a pure strategy of using only single or team drivers.

A fundamental finding of our experimental results is that cost reasons alone cannot justify to operate all vehicles with single drivers. This observation already contradicts common practice in many transport companies not using team drivers at all. Operating a fleet with a mix of team and single drivers can results in significant cost savings in a market with very low profit margins. It must be noted that this observation also holds for high-income countries where transport managers might hesitate in assigning team drivers to a vehicle assuming that the respective costs cannot be justified.

Not surprisingly the highest cost benefit is obtained if team drivers can parallelize service tasks at customer locations. However, an interesting finding of

our experiments is that even if team drivers cannot parallelize service tasks and require the same amount of time for servicing customers as a single driver, the cost advantage of operating some vehicles with a team of two drivers can be significant. In many cases the average cost savings are a multitude higher than average profit margins in European road freight transport.

Using team drivers for selected routes does not necessarily imply that more drivers are needed. Our computational experiments reveal that in some cases the number of driver salaries that must be paid is actually smaller, because of the shorter duration of the team driver routes. In other cases, however, more drivers are needed. In the presence of driver shortages this may be a disadvantage, however, the cost benefits of using a mix of single and team drivers can be reinvested into driver salaries, making the truck driver job more attractive. Furthermore, some truck drivers prefer team driving due to safety and security benefits and having a companion while being en-route.

The best share of team drivers can vary significantly for different use cases. Obviously, if all routes can be operated by a single driver on a single day, it is not possible to reduce costs by using team drivers without changing the routes. On the other hand, if team drivers are required, e.g. due to security concerns or because loading and unloading involves heavy work, there is no choice of using a single driver. For cases where team drivers are required for some customers, our approach can be easily adapted by simply reducing the set R_1 to the set of feasible routes that do not contain a customer requiring team drivers. In such cases, our approach would become even faster because fewer single-driver routes would have to be evaluated.

Obviously, there is a myriad of different operational requirements in road freight transport and it is impossible to conduct experiments that capture all of these requirements in all different combinations. Our solution approach for simultaneous optimization of driver assignments, routes, and schedules can be used for a large variety of these characteristics. Whenever normative driving patterns cannot be used to decide on single vs. team driving, transport managers can use the proposed methodology, or an adaptation thereof, to determine how many drivers are required and which routes should be operated by single or team drivers.

Crewing decisions can interrelate with other tactical decisions. In such situations, our approach can be used in a what-if analysis, where various tactical decisions interrelating with crewing decisions are evaluated using simulation and optimization. It must be noted that the full potential of team driving may be realized only if certain tactical decisions are changed, making it possible to operate longer routes with a team of two drivers. Otherwise, the inherent bias resulting from prior tactical decisions based on a single-driver practice can lead to optimized crew sizes involving only a limited number of team drivers. This can be seen in our results on the instances derived from a real-life business of one of ORTEC's customers, which historically relied exclusively on single drivers. These instances are influenced by several tactical decisions of the retailer, such as the selected delivery locations, the assignment of delivery locations to distribution centers, and the choice of visit days and times. Nevertheless, our experiments showed that even in such cases a notable cost reduction can be obtained by assigning team drivers to some of the vehicles. By

reconsidering some of the tactical decisions, an even higher benefit of team driving could be possible.

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Appendix A: Truck driver scheduling for team drivers

Let us assume we are a given route $(n_1, n_2, \ldots, n_k)$, where n_i indicates a location at which a stationary task of duration s_i has to be conducted with a start time in the given time window $[t_i^{\min}, t_i^{\max}]$. The driving time from a node n to a node m in the route is denoted by d_{nm}. We can determine a schedule for a team of two drivers minimising the number of working days required by a labelling method in which the state of the driver team is represented by labels

$$l = (l^{\text{time}}, l^{\text{trip}}, l^{\text{begin}}, l^{\text{postpone}}, l^{\text{drive}}, l^{\text{work}}, l^{\text{elapsed}}, l^{\text{latest}})$$

where

l^{time}	represents the current time,
l^{trip}	represents the driving time required until the next customer,
l^{begin}	represents the start time,
l^{postpone}	represents the latest possible start time,
l^{drive}	represents the cumulated driving time of both drivers since the last rest,
l^{work}	represents the cumulated working time of both drivers since the last rest,
l^{elapsed}	represents the time elapsed since the end of the last rest,
l^{latest}	represents the latest possible time until which the last rest must be fully taken.

The labelling method starts with an initial label

$$l = (t_{n_1}^{\min} + s_{n_1}, 0, t_{n_1}^{\min}, t_{n_1}^{\max}, 0, s_{n_1}, s_{n_1}, t_{n_1}^{\max})$$

representing the state of the drivers after conducting the stationary task at location n_1 and extends labels along the arcs of an auxiliary network similar to the one

Table 7 REFs for team drivers

$\hat{l}$	$f_{nm}^{\text{trip}}(l)$	$f_{\Delta}^{\text{drive}}(l)$	$f_{\Delta}^{\text{offduty\|rest}}(l)$	$f_{m}^{\text{visit}}(l)$
$\hat{l}^{\text{time}}$		$l^{\text{time}} + \Delta$	$l^{\text{time}} + \Delta$	$\max\{l^{\text{time}}, t_m^{\min}\} + s_m$
$\hat{l}^{\text{trip}}$	d_{nm}	$l^{\text{trip}} - \Delta$		
$\hat{l}^{\text{begin}}$				$\min\left\{l^{\text{begin}} + \max\{0, t^{\min} - l^{\text{time}}\}, l^{\text{postpone}}\right\},$
$\hat{l}^{\text{postpone}}$				$\min\{l^{\text{postpone}}, t_m^{\max} - (l^{\text{time}} - l^{\text{begin}})\}$
$\hat{l}^{\text{drive}}$		$l^{\text{drive}} + \Delta$	0	
$\hat{l}^{\text{work}}$		$l^{\text{work}} + \Delta$	0	$l^{\text{work}} + s_m$
$\hat{l}^{\text{elapsed}}$		$l^{\text{elapsed}} + \Delta$	0	$\max\{l^{\text{elapsed}}, t_m^{\min} - l^{\text{latest}}\} + s_m$
$\hat{l}^{\text{latest}}$			∞	$\min\{l^{\text{latest}}, t_m^{\max} + s_m - \hat{l}^{\text{elapsed}}\}$

illustrated in Fig. 8. First, the label is extended with REF $f_{n_1 n_2}^{\text{trip}}$ associated to the link from location n_1 to an intermediate vertex. This REF is used to set the required driving time between n_1 and n_2. Then, the path can continue along the loops where the REFs $f_{\Delta}^{\text{drive}}$ and $f_{\Delta}^{\text{offduty|rest}}$ are used to update the driver state depending on the duration Δ of the respective activity. Eventually, the path continues along an arc from the intermediate vertex to location n_2 and REF $f_{n_2}^{\text{visit}}$ is used to update the label considering the stationary work that is conducted at location n_2. This approach is repeated until the stationary work of the last location is completed.

Table 7 shows how label attributes are updated by the REFs. Empty entries in the table indicate that the respective values of the label attributes remain unchanged.

The REF f_{nm}^{trip} initializes the required driving time for the trip to d_{nm} and leaves all other label attributes unchanged. The REF $f_{\Delta}^{\text{drive}}$ reduces the remaining driving time by the duration of the driving activity Δ, increases the time, the cumulative amounts of driving and work, and the time elapsed since the last rest by Δ. The REF $f_{\Delta}^{\text{offduty|rest}}$ increases the time attribute by the duration Δ, sets the cumulative amount of driving and work to zero, and sets the time elapsed since the last rest to zero and the latest possible completion time of the rest to infinity. The REF f_{m}^{visit} increases the time attribute to the earliest time at which the stationary work at customer m can be completed and adds the duration of the stationary work to l^{work}. If $l^{\text{time}} < t_m^{\min}$, then the start time may be increased in order to avoid waiting time before location m. Similarly, the latest possible start time may be reduced if the end of the time window at location m requires so. Furthermore, the duration of the previous rest period is increased by the smallest possible amount so that

Table 8 Feasibility conditions

REF	Feasibility condition
$f_{\Delta}^{\text{drive}}(l)$	$\Delta \le \min\{l^{\text{trip}}, 18 - l^{\text{drive}}, 20 - l^{\text{work}}, 21 - l^{\text{elapsed}}\}$
$f_{m}^{\text{visit}}(l)$	$l^{\text{trip}} = 0, l^{\text{time}} \le t_m^{\max}, s_m \le 20 - l^{\text{work}},$ $\max\{l^{\text{elapsed}}, t_m^{\min} - l^{\text{latest}}\} + s_m \le 21$
$f_{\Delta}^{\text{offduty\|rest}}(l)$	$\Delta \ge 9$

the time elapsed is not unnecessarily increased and that the work can start within the time window of the customer. The time elapsed since the last rest is updated accordingly and the latest completion time of the previous rest is reduced if the closing time of the time window requires this.

In order to only consider labels complying with the regulations, the feasibility conditions given in Table 8 must be satisfied when using any of the REFs.

For REF $f_{\Delta}^{\text{drive}}$ the cumulative driving time must not exceed two times 9 h, the cumulative working time must not exceed two times 10 h, and it must be possible to take 9 h of rest within 30 h after the last rest. For REF f_{m}^{visit} the customer location must have been reached, the time window must not be closed, the limit on the cumulative working time must not be exceeded, and it must be possible to take 9 h of rest within 30 h after completion of the last rest. For REFs $f_{\Delta}^{\text{offduty|rest}}$ the duration Δ must be at least 9 h.

The large number of alternative labels that may be generated in the process of finding a truck driver schedule for a route $(n_1, n_2, \ldots, n_k)$ can cause a significant computational burden. In order to avoid unnecessary calculations, dominance criteria can be used to discard a large share of labels. Given two feasible labels l_1 and l_2 which both represent a driver state at the end of the partial route $(n_1, n_2, \ldots, n_i)$ with $1 \leq i \leq k$, we write $l_1 \preceq l_2$ if

$$
\begin{aligned}
l_1^{\text{time}} &\leq l_2^{\text{time}},\\
l_1^{\text{trip}} &\leq l_2^{\text{trip}},\\
\left\lfloor \frac{l_1^{\text{begin}}}{24} \right\rfloor &\geq \left\lfloor \frac{l_2^{\text{begin}}}{24} \right\rfloor,\\
\left\lfloor \frac{l_1^{\text{postpone}}}{24} \right\rfloor &\geq \left\lfloor \frac{l_2^{\text{postpone}}}{24} \right\rfloor,\\
l_1^{\text{drive}} &\leq l_2^{\text{drive}},\\
l_1^{\text{work}} &\leq l_2^{\text{work}},\\
l_1^{\text{elapsed}} &\leq l_2^{\text{elapsed}},
\end{aligned}
$$

and

$$
l_1^{\text{latest}} \geq l_2^{\text{latest}}.
$$

The division by 24 h for attributes l^{begin} and l^{postpone} and subsequent truncation, together with $l_1^{\text{time}} \leq l_2^{\text{time}}$, ensures that the number of working days of any schedule obtained by extending l_1 does not exeeced the number of working days of any schedule obtained by extending l_2.

If $l_1 \preceq l_2$ then l_2 can be discarded because it can not contribute to finding a schedule for the given route with lower costs.

With these dominance criteria we can show that an optimal truck driver schedule can be found if the parameter Δ for REF $f_{\Delta}^{\text{drive}}(l)$ is always set to

$$\Delta_l := \min\{l^{\text{trip}}, 18 - l^{\text{drive}}, 20 - l^{\text{work}}, 21 - l^{\text{elapsed}}\}$$

and the the parameter Δ for REF $f_{\Delta}^{\text{offduty|rest}}(l)$ is always set to 9 h.

After having found a non-dominated label representing the state of the team drivers after traversing the auxiliary network, we can determine the minimal number of days required as follows. If $\left\lceil \frac{l^{\text{begin}}}{24} \right\rceil \leq l^{\text{postpone}}$, we can postpone the start time so that it begins at the next day. If furthermore $\left\lceil \frac{l^{\text{time}}}{24} \right\rceil - l^{\text{time}} < \left\lceil \frac{l^{\text{begin}}}{24} \right\rceil - l^{\text{begin}}$ we can postpone the start time to the beginning of the next day without pushing the completion time into the next day.

Appendix B: Evaluation of speed-up techniques

Table 9 provides the the running times of our algorithm without the speed-up techniques described in Sect. 4.4 divided by the running times of our algorithm with the speed-up techniques. The artificial instances described in Sect. 5 with cost factors $c^{\text{driver}} = 100$, $c^{\text{truck}} = 100$, and $c^{\text{distance}} = 0.25$ were used for these experiments.

Table 9 Speed-up factors

Instance	Without memory structures	Without lower bounds	Without memory structures and lower bounds
R101	3.77	3.06	19.76
R102	4.08	3.36	23.15
R103	3.43	3.78	15.70
R104	3.20	3.76	17.16
R105	4.21	2.59	20.01
R106	3.77	3.29	17.89
R107	3.34	3.11	16.39
R108	3.96	3.24	21.66
R109	3.49	2.89	15.10
R110	3.20	3.02	14.38
R111	3.66	3.25	17.86
R112	3.85	2.54	15.83
R201	3.52	2.72	15.84
R202	3.11	3.19	14.40
R203	3.41	3.07	16.89
R204	3.45	2.91	13.99
R205	3.26	2.69	16.00
R206	2.86	3.26	11.58
R207	3.87	2.86	19.21
R208	2.99	3.03	12.51
R210	2.92	3.16	11.87
R209	3.35	2.77	14.33
R211	2.53	2.98	13.16
C101	5.07	2.48	27.02
C102	4.40	3.42	23.78
C103	3.51	4.05	18.60
C104	4.13	3.94	22.70
C105	4.87	2.92	25.13
C106	4.31	2.91	23.65
C107	3.90	3.22	21.83
C108	3.91	2.82	19.79
C109	3.96	3.28	21.92
C201	6.25	2.19	14.00
C202	5.04	2.33	11.35
C203	4.46	2.42	10.38
C204	3.43	2.77	9.66
C205	8.44	1.79	10.86
C206	5.84	2.04	11.69
C207	5.27	2.26	11.63
C208	6.38	1.89	9.97
RC101	5.52	2.76	28.87
RC102	4.45	3.24	26.72

Table 9 (continued)

Instance	Without memory structures	Without lower bounds	Without memory structures and lower bounds
RC103	4.18	3.18	26.66
RC104	3.93	3.97	26.76
RC105	4.78	2.78	28.98
RC106	3.69	3.17	17.95
RC107	4.18	2.77	24.53
RC108	4.26	3.17	26.79
RC201	3.67	2.60	17.15
RC202	3.90	2.76	21.97
RC203	3.22	2.85	18.08
RC204	3.67	3.07	15.78
RC205	3.49	2.73	18.85
RC206	3.82	2.39	18.07
RC207	3.09	3.03	15.85
RC208	3.40	2.75	19.57
Average	2.94	4.03	18.24

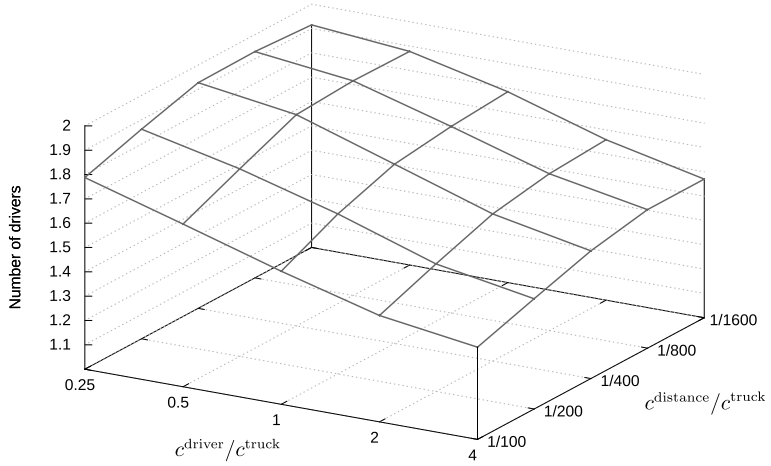


Fig. 16 Average number of drivers for modified Solomon instances for $s^{\text{team}} = 0.5 \cdot s^{\text{single}}$

Appendix C: Results for the full factorial design

Figures 16, 17 and 18 show the average number of drivers per vehicle in the solutions obtained for the different cost parameters and assumptions on service durations. Figures 19, 20 and 21 show the relative cost increase of pure strategies using single drivers or team drivers only compared to a mix strategy for the different cost

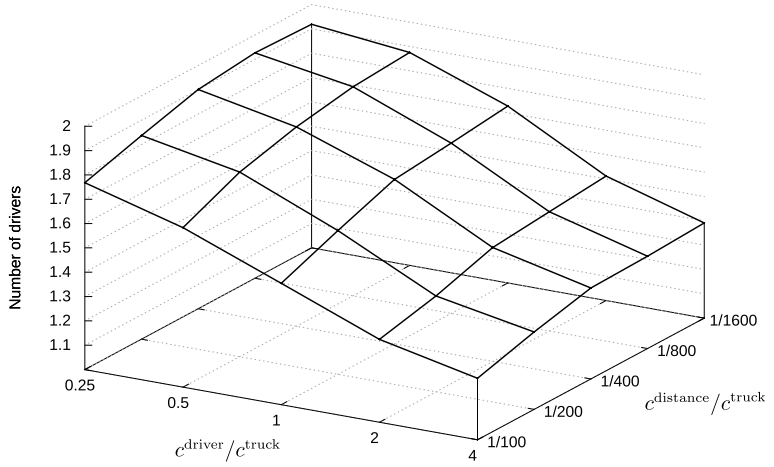


Fig. 17 Average number of drivers for modified Solomon instances for $s^{\text{team}} = 0.75 \cdot s^{\text{single}}$

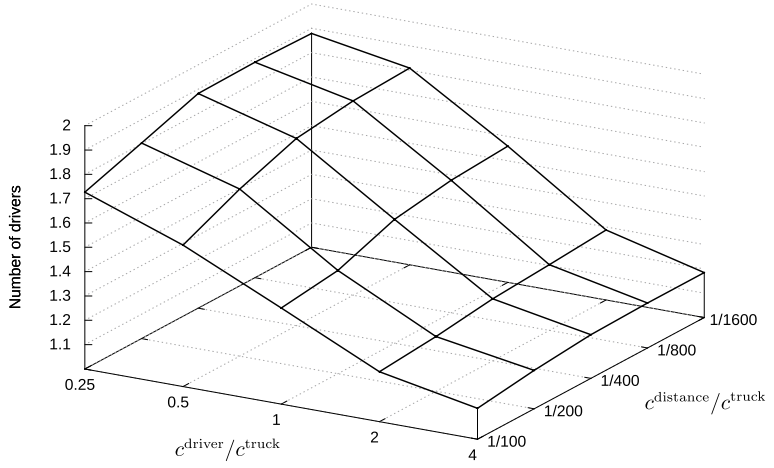


Fig. 18 Average number of drivers for modified Solomon instances for $s^{\text{team}} = s^{\text{single}}$

parameters and assumptions on service durations. In the figures, an increase in driver cost corresponds to a move from the left to the right, an increase in mileage cost corresponds to a move to back to the front, and an increase in vehicle cost corresponds to a move from the front right to the back left.

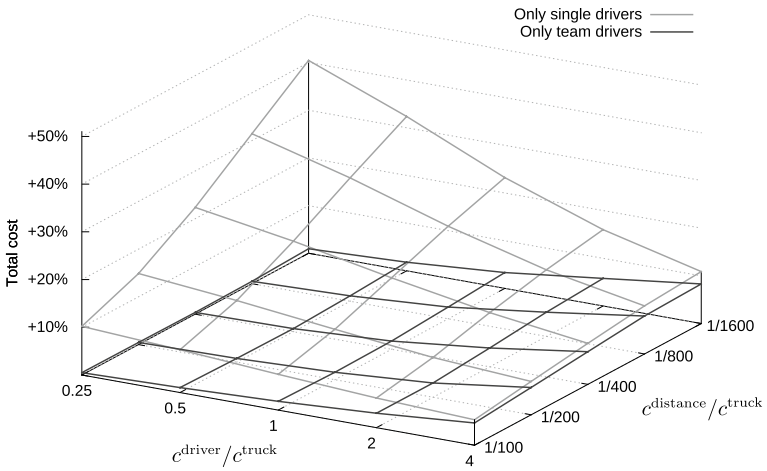


Fig. 19 Average cost difference for modified Solomon instances for $s^{\text{team}} = 0.5 \cdot s^{\text{single}}$

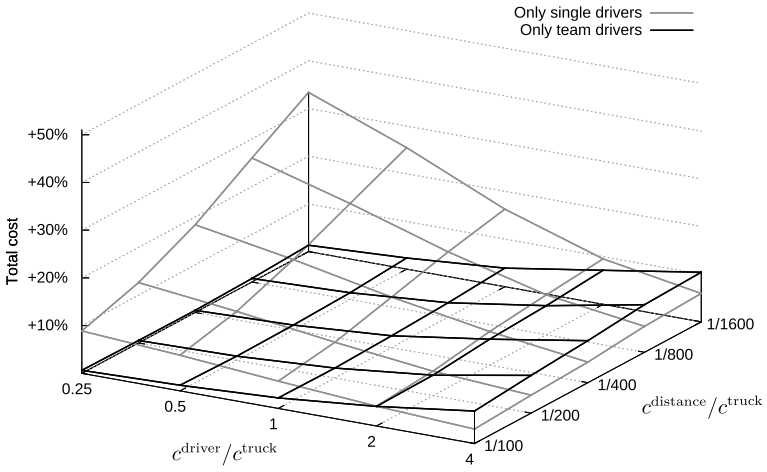


Fig. 20 Average cost difference for modified Solomon instances for $s^{\text{team}} = 0.75 \cdot s^{\text{single}}$

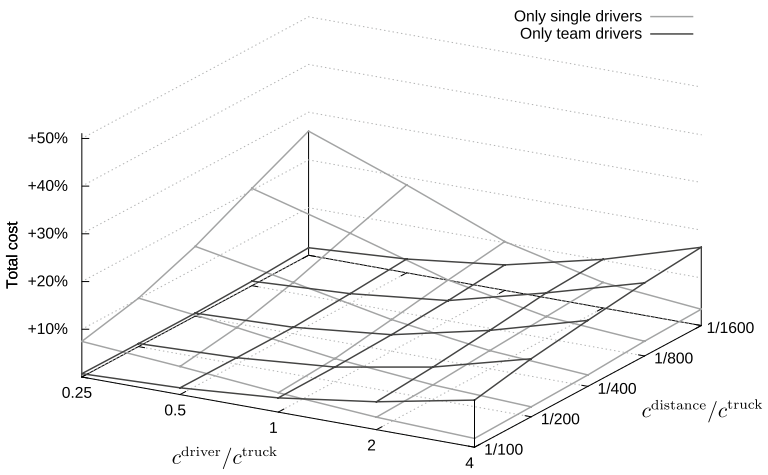


Fig. 21 Average cost difference for modified Solomon instances for $s^{\text{team}} = s^{\text{single}}$

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