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ORIGINAL PAPER

Energy vehicle routing problem for differently sized and powered vehicles

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Abstract Electric vehicles (EVs) and combustion-powered vehicles (CVs) differ substantially with respect to several characteristic factors that have major impacts on vehicle routing. EVs are more energy efficient than CVs, but they have a shorter driving range, and compared to CVs with the same gross weight, they have a lower payload. In this paper, various vehicle fleets with differently sized EVs and CVs are considered for vehicle routing. First, EVs are opposed to CVs. Second, the effect of increasing the battery capacity of EVs is investigated. Third, the impact of introducing recharge stations for EVs is analyzed. Finally, the characteristics of mixed fleets are investigated. The computational results are generated by solving a MIP formulation of the introduced Energy Vehicle Routing Problem with Time Windows, Recharge Stations and Vehicle Classes (EVRPTW-R-VC) by means of a commercial solver.

Keywords Vehicle routing · Electric powered and combustion-powered vehicles · Heterogeneous vehicle fleet · Energy consumption · Recharge stations

JEL Classification C0 · R4

1 Introduction

The environmental impact of entrepreneurial activities has become increasingly crucial in recent years. This development has led to political reforms and incentives by subsides which are projected to reduce the quantity of emitted

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greenhouse gases and their effect on global warming. Furthermore, a company's current reputation also depends on its engagement in environmental activities. In particular, the transportation sector intends to reduce its energy consumption and emissions by applying new technologies. Thus, a discussion has begun regarding the private and commercial use of electric powered vehicles (EVs). On 1 January 2017, 311 EVs with a gross weight over 2 tons were registered in Germany (Kraftfahrt-Bundesamt 2017). This documents that few trucking companies have recently started using EVs (Berndt 2016). Of course, they do not entirely abandon their conventional fleet but they replace some of their combustion-powered vehicles (CVs) by EVs to reduce their overall energy consumption and emissions (oV 2015). Dispatchers need time to get used to routing and scheduling EVs, especially for handling the new challenges which are coming up by EVs. The small driving range caused by a limited battery capacity may be the most problematic attribute of EVs. Thus, the field application of EVs is restricted to relatively short tours unless an exchange or recharge of the vehicles' batteries takes place. Furthermore, the battery weight leads to a reduction of payload; this is an additional challenge in the transportation sector. From a financial perspective, it is important to note that the fixed and variable costs of EVs and CVs differ considerably. Especially, the investment costs of EVs are significantly higher than the investment costs of CVs. Nevertheless, currently there are cost advantages for EVs operated in rural areas for delivery services with driving ranges of approximately 100 km (Kopfer and Schopka 2016). In addition, in the foreseeable future, these cost advantages will become more significant due to the expected technological development (Hacker et al. 2015).

Currently, EVs are used for urban and local rural transport only; the utilization of recharge stations during a tour is mostly avoided. Since the network of recharge stations is scarce, extra travel time and distance are often required to visit such a station; furthermore, considerable additional time is needed for recharging. In sum, the on-tour utilization of recharge stations is associated with a loss of time and an increase in costs. The costs of a route consist largely of the drivers' wages; thus, from an economic perspective, idle time for a vehicle and its driver should be avoided. Another option would be the utilization of recharge stations which are provided at the customer locations. Then, the recharge operation can be done during the service operation. However, in this case, precise agreements and cooperation are necessary, e.g., for the payment of the used electricity and the reservation of customer-owned recharge stations; furthermore, the time spent at a customer location may increase, since the time needed for recharging often would exceed the service time.

EVs are more energy efficient than CVs, but they can only operate within a smaller range and have a lower payload than CVs. Consequently, the exchange of a combustion-powered fleet for a pure electric powered vehicle fleet leads to a reduction of the solution space for routing and scheduling. Mixed fleets with EVs and CVs lead to routing problems that are heterogeneous with respect to both restrictions and the objective function of the corresponding optimization models; therefore, research on the fleet size and the utilization of mixed vehicle fleets require new specific investigations (Hiermann et al. 2016). First of all, an analysis of the strengths and shortcomings of differently composed fleets under the consideration of the specific characteristics of EVs and CVs is needed.

In this study, different types of fleets are considered. Fleets with CVs are opposed to fleets with EVs; homogeneous fleets with vehicles of different size and different types of powering are opposed to each other; and then the homogeneous fleets are opposed to a heterogeneous fleet composed of differently sized EVs and CVs. First, we analyze the effect of using EVs instead of CVs on the feasibility and quality of transportation plans. For this analysis, we consider two optimization goals: energy minimization and travel time minimization. Second, the effect of increasing the battery capacity of EVs is investigated. Third, the impact of introducing recharge stations is analyzed. The question is whether the possibility of refilling batteries during the execution of tours has a positive effect on the transportation plans for EVs. For the computational experiments, a MIP formulation of the Energy Vehicle Routing Problem with Time Windows, Recharge Stations and Vehicle Classes (EVRPTW-R-VC) is developed. This energy model is a comprehensive extension of the well-known Vehicle Routing Problem (VRP), which was originally introduced by Dantzig and Ramser (1959).

This paper is structured as follows. Section 2 presents an overview of the recent literature. The vehicle-specific characteristics of the considered vehicle types are presented in Sect. 3. A MIP formulation for the EVRPTW-R-VC is described in Sect. 4. Section 5 presents computational studies regarding the utilization of various vehicle fleets in different scenarios with and without recharge stations. Additionally, EVs with differently sized batteries are considered. Finally, we conclude this study in Sect. 6.

2 Literature review: emission and energy minimization

In recent years, environmental aspects have become crucial, and the quantity of the related recent research on vehicle routing has increased. A survey on green VRPs is presented by Lin et al. (2014). A summary of VRPs regarding the reduction of environmental pollution of CVs is published by Toth and Vigo (2014). Furthermore, we refer to the review on green road freight transportation by Demir et al. (2014) and to the comprehensive review by Eglese and Bektaş (2014).

2.1 Combustion vehicles

In the literature, there exist several approaches for vehicle routing based on objective functions, which minimize the amount of Greenhouse Gases (GHGs) instead of costs. The Emission Vehicle Routing Problem is introduced by Figliozzi (2010), who studied the minimization of CO_2 emissions and fuel consumption on an extension of the classical VRP. A mathematical formulation and a heuristic approach is proposed to solve this problem; computational experiments demonstrate that, relative to the classical VRP, significant emission savings are possible.

An analysis of the impact of road gradient and payload is conducted by Scott et al. (2010) within a CO_2 minimizing vehicle routing approach. Four vehicle types are considered, and the effect of gradient and payload on specific vehicle types is discussed. The instances used for a modified traveling salesman problem are based on real life examples. Suzuki (2011) analyzes the effect of payload also by means of experiments on the traveling salesman problem. Based on computational studies, Suzuki (2011) finds that delivering heavy goods early in a tour can be worthwhile with respect to fuel consumption.

The energy minimizing vehicle routing problem was introduced by Kara et al. (2007). The objective is to generate transportation plans which induce minimal cargo (measured in ton-kilometers) to fulfill transportation requests. Thus, the amount of used energy can be reduced in comparison to distance minimization.

The Pollution Routing Problem with and without time windows is proposed by Bektaş and Laporte (2011). In this paper several mathematical models are developed with different objective functions such as minimizing distance, weight load, energy or costs. Their energy minimizing objective function refers to speed and payload, which are the most influential factors on emissions. In a computational study, all described models are compared to each other.

An extension of the classical VRP by introducing fuel costs, carbon emission costs and vehicle usage costs is done by Zhang et al. (2015). The developed tabu search algorithm incorporates distance, load and speed simultaneously. The computational study shows that route and vehicle arrangements based on minimal fuel consumption are economically and environmentally friendly.

Koç et al. (2014) investigate the fleet size and mix pollution-routing problem to quantify the benefits of using a flexible fleet with respect to fuel consumption, emissions and costs. Speed optimization is an important part in this work. Nevertheless, their tests demonstrate that using a heterogeneous fleet without speed optimization allows for higher benefits than using a homogeneous vehicle fleet with speed optimization. In the literature, few approaches exist for investigating vehicle routing with the specific goal of minimizing GHG emissions of a mixed vehicle fleet. An extensive review on vehicle routing with cost and emission objectives for heterogeneous vehicle fleets is given by Koç et al. (2016). They classify and summarize the existing literature on heterogeneous vehicle routing problems of the last 30 years.

Kwon et al. (2013) consider a heterogeneous vehicle fleet with the objective of minimizing carbon emissions. By their mathematical model a cost-benefit assessment of the price for purchasing or selling carbon emission rights can be made. They develop and apply tabu search algorithms for their experiments and demonstrate that the amount of carbon emissions can be decreased through carbon trading without increasing the transportation costs.

Kopfer et al. (2014) investigate the Emission Vehicle Routing Problem with Vehicle Classes and extend the work which was introduced in Kopfer and Kopfer (2013). Four vehicle types with a gross weight of 3.5, 7.5, 12 and 40 tons are included in their study. The researchers demonstrate that, through the utilization of a heterogeneous vehicle fleet, significant reductions (to a maximum of 20%) in emissions are possible, especially if the customer requests are small. In particular, they prove that fragmenting a tour into several smaller tours for vehicles of different size can result in a considerable reduction of emissions. However, fragmentation of tours causes increased travel distances and an increase in the number of routes.

Vornhusen and Kopfer (2015) consider mixed fleets with six different types of CVs. Additionally, they introduce the option of split delivery into the problem considered by Kopfer et al. (2014). Their experiments show that the emitted GHGs can be reduced further by allowing split deliveries and by using an adapted heterogeneous fleet with six vehicle types for transportation.

2.2 Electric vehicles

A discussion on EVs used for cargo is provided by Pelletier et al. (2014). The researchers provide an overview on existing research on vehicle routing for EVs. Additionally, they summarize the technical and marketing background related to this topic; they also discuss the future technological perspectives.

A Green Vehicle Routing Problem is described by Erdoğan and Miller-Hooks (2012). The developed techniques adress the difficulties that exist for alternatively powered vehicles, such as the scarce net for stocking up energy and the limited driving range. A MIP-model is formulated, and two construction heuristics are provided. Schneider et al. (2014) adapt the Green Vehicle Routing Problem to EVs and add time window constraints. Thus, the required time for a recharging process depends on the state of the remaining charge. The researchers solve the problem with a Variable Neighborhood Search approach using tabu search as local optimization technique with the objective to satisfy charge constraints and time window constraints.

Desaulniers et al. (2016) consider four Scenarios of the VRPTW including EVs and recharge stations. They investigate the effects if only one or multiple recharge stations can be visited within a route and they consider scenarios in which the battery is fully or partially charged at the recharge stations. For their computations experiments an exact Branch-Price-and-Cut algorithm is used. The results show that through the option of partial and multiple charging operations a reduction of the travel costs and the amount of required vehicles is possible compared to the scenario in which exactly one fully charging operation is allowed.

Keskin and Çatay (2016) investigate a routing problem for EVs and enable a partially charging of the battery during the execution of a tour. To solve their problem an Adaptive Large Neighborhood Search algorithms is used. Through their computational experiments it is shown that the algorithm performs very well and that a partially charging operation can increase the quality of the routes.

Wang and Lin (2013) consider different types of recharge stations, i.e. usual charging stations and fast charging stations. A sensitivity analysis shows that an increasing driving range of a vehicle leads to a reduction of required recharge stations to obtain feasible solution plans

Sassi et al. (2014) provide a mathematical formulation of a VRP with a mixed fleet of combustion and battery powered vehicles with time-dependent costs for charging operations. The objective minimizes the amount of used vehicles as well as transportation costs and charging costs. They are using two different heuristic approaches to solve their problem. However, no information is given on the capacity of the vehicles.

The electric fleet size and mix vehicle routing problem with time windows and recharge stations is proposed by Hiermann et al. (2016). A MIP formulation is presented in the researcher's study as well as an ALNS to solve benchmark instances. In their routing problem, several EVs with different capacities and costs are provided. To increase the scope of travel distances that can be accomplished by these vehicles, several recharge stations are integrated in their instances. Their study shows that at most one recharge station is visited per vehicle on its tour. The provision of a mixed fleet with several EVs leads to benefits compared to a homogeneous fleet of one electric vehicle type.

A study to compare EVs and CVs is performed by Kopfer and Schopka (2016). They investigate the strengths of CVs (driving range, number of used vehicles, ability of feasible routing plans) and the advantages of EVs (energy efficiency, GHG emissions) and present initial experiments on a mixed fleet of both types of vehicles.

Goeke and Schneider (2015) propose and evaluate an Adaptive Large Neighborhood Search algorithm for a VRP with time windows and a mixed fleet of EVs and CVs. The researchers investigate the effect of considering the actual cargo load distribution on the structure and quality of the generated solutions; they also study the influence of three different objective functions on solution attributes and on the contribution of EVs to the overall routing costs. The considered objectives refer to (1) travel time, (2) cost for vehicle propulsion and labor, and (3) vehicle and labor cost augmented by costs for battery replacement. In contrast to our study, they assume that all vehicles (EVs and CVs) have the same cargo loading capacity; in addition, they do not consider vehicles of different size.

3 Vehicle characteristics

The comparison of vehicles powered by electric and combustion engines is complex, as different kinds of energy sources are used by these vehicles. An EV is consuming electric power supplied by a battery. The amount of electric power consumed is measured in kWh. A combustion engine is supplied with energy by consuming a specific type of fuel. In this case, the amount of consumed energy is quantified by the required volume of fuel, measured in liters. To enable a comparison of both differently powered vehicle types, conversion factors for transforming the different

Table 1 Conversion factors according to DIN EN 16258 (Schmied and Knörr, 2013)

	Unit	TTW	WTW
Diesel (no biodiesel)	MJ/l	35.9	42.7
Diesel Germany	MJ/l	35.7	44.4
Electricity Germany	MJ/kWh	3.6	9.7

kinds of energy to a common measuring unit are necessary. In Table 1, factors are shown that enable the conversion of one liter of diesel and one kWh of electricity into the standardized unit for energy consumption [megajoules (MJ)]. Energy consumption can be measured either by Tank-to-Wheel (TTW) or by Well-to-Wheel (WTW) method (Schmied and Knörr 2013).

Utilization of EVs in the transportation sector is characterized by the reduced loading capacity of EVs and their limited driving range. The driving range of EVs depends on the capacity of the installed battery, amongst other factors. In automotive construction, lithium-ion batteries are usually used because of their advantages in battery weight and security (Orten 2016). Several types of lithium-ion batteries, which differ in their energy density, exist. A lithium iron phosphate battery provides an energy density of approximately 100 Wh/kg (Wiki 2016).

Particularly for large trucks with a gross weight of 40 tons, only a few examples of using electric power exist. One example for a specific field application is a shuttle between a manufacturer and a nearby supplier (Pieringer 2015). In general, however, the usage of large electric trucks currently is impracticable and appears to remain inefficient in the medium term, particularly since such vehicles are primarily used for long-distance cargo. The usage of small vans in city logistics is becoming increasingly more familiar. However, in practice, the usage of medium-sized vehicles has only recently begun; therefore, our study refers to the challenging research question of using medium-size EVs that are used for medium- and short-distance cargo.

In this paper, four vehicle types are considered: two EVs and two CVs. We consider the following two electric vehicle types that are mainly used in our field of application: EVs with a gross weight of 7.5 and 18 tons. Hereafter, these vehicle types are denoted as $EV(7.5)$ and $EV(18)$, respectively. To compare the transportation plans of EVs with corresponding CVs, two types of CVs with 7.5 tons gross weight [denoted as $CV(7.5)$] and 18 tons gross weight [denoted as $CV(18)$] are introduced. Table 2 specifies the characteristics of the vehicles considered in this study, which correspond to the manufacturers' specifications (Orten 2016; E-Force One AG 2016).

Table 2 Characteristics of CVs and EVs

Vehicle type	$CV(7.5)$	$EV(7.5)$	$CV(18)$	$EV(18)$
Traction				
Energy type	Diesel	Electric	Diesel	Electric
Energy content	70 l	62 kWh	200 l	2 × 120 kWh
Maximal range	450 km	130 km	1200 km	300 km
Weights				
Empty weight	3.5 tons	4 tons	9 tons	12 tons
Payload	4 tons	3.5 tons	9 tons	6 tons
Energy consumption (per 100 km)				
Empty vehicle	13 l	44 kWh	18 l	80 kWh
Loaded vehicle	16.2 l	63 kWh	24 l	95 kWh

It is widely accepted that the following Eq. (1) is an appropriate and reasonably simplified approximation for the expected energy consumption $F_k(i,j)$ of a truck k carrying a payload of weight q_{ij} from a location i to a location j with d_{ij} representing the travel distance for the non-stop travel between i to j (Xiao et al. 2012; Kopfer et al. 2014; Vornhusen and Kopfer 2015).

$$F_k(i,j) = \left(a_k + b_k \cdot q_{ij}\right) \cdot d_{ij} \tag{1}$$

In Eq. (1), a_k denotes the parameter for the energy required by an empty driving vehicle of type k per kilometer, whereby b_k defines the parameter for the required energy per ton payload and kilometer. The values for a_k and b_k substantially differ for CVs and EVs. In Table 3, the values for all considered vehicle types are standardized by using the conversion factors for the WTW values presented in Table 1. In this study, WTW is used for conversion since it provides a more comprehensive and realistic account for energy consumption and CO_2 emissions than TTW. Table 3 additionally shows the total energy content E_k of the full tank or full battery of vehicle k. Finally, the maximum tour length T_k for vehicle k (measured in km) is provided in Table 3. For the field applications considered in our study, T_k refers to the daily tour length. The directives for maximal working hours and the EC regulations for drivers' driving hours result in a limitation of the maximal daily travel distance of single-manned vehicles. The maximal tour length specified for EVs and CVs in Table 3 depends on the average speed of the vehicles during their tour, and on the number and duration of stops. Since we assume that smaller vehicles usually fulfill tours with more stops than larger vehicles, the maximal tour length is set to values that are more restrictive for vehicles with 7.5 ton gross weight than for those with 18 ton gross weight. The actual daily travel distance of a CV k is only limited by T_k, as its amount of available energy E_k is not restrictive for daily operations. If en route recharging is excluded, the tour length of an EV is restricted by E_k, as an EV cannot achieve the maximal tour length T_k without recharging its battery.

In this paper, we consider planning situations with and without the possibility of en route recharging. The vehicles' batteries are loaded by 100% when the vehicles are leaving the depot. We assume that en route recharging will only be possible at service stations for recharging; in other words, the option of recharging at customer locations is excluded. During the execution of a delivery tour, only rapid recharge operations at special recharge stations are considered; therefore we assume a required time for the recharge operation of 1 h, which is acceptable and a reasonable simplification for vehicle routing. However, at recharge stations a battery is only charged to a maximum of 80% of its total battery capacity since, at the end of a charging operation, the charging

Table 3 Parameters of the vehicle types

	$CV(7.5)$	$CV(18)$	$EV(7.5)$	$EV(18)$
$a_k\,[\frac{\text{MJ}}{\text{km}}]$	5.772	7.992	4.268	7.760
$b_k\,[\frac{\text{MJ}}{\text{tkm}}]$	0.3552	0.2960	0.5266	0.2425
E_k [MJ]	3108	8880	601	2328
T_k [km]	450	500	450	500

power must be reduced to avoid an overloading of the batteries. Thus, the last phase of a charging operation is omitted since it would take the longest time (Pelletier et al. 2017).

4 Mathematical model

In this study the EVRPTW-R-VC describes an extended vehicle routing problem providing an objective function that minimizes the total amount of required energy. Furthermore, the vehicles are allowed to visit recharge stations. Every recharge station can be visited more than once in a route and, in addition, each recharge station can be used in several routes from different vehicles. This requires a specific mathematical formulation of the EVRPTW-R-VC to track the vehicle's load and visiting times at the customer nodes within predefined time windows. The EVRPTW-R-VC can be represented on a complete, undirected graph $G = (N, A)$. This graph is specified through the set of nodes N and the set of arcs $A = N \times N$. The set of nodes $N = C \cup D \cup R$ represents the customer locations ($C = \{1, ..., n\}$), the duplicated depot ($D = \{0, n + 1\}$) and the recharge stations ($R = \{n + 1 + 1, ..., n + 1 + r\}$). At the depot, a fleet of vehicles is stationed and given as the set $K = \{1, ..., k\}$. Each vehicle has a specific loading capacity Q_k. Each arc $(i,j) \in A$ is associated with a travel distance d_{ij} and a travel time t_{ij} with $t_{ij} = d_{ij}/v$, whereby v defines the constant average speed of a vehicle. All nodes $i \in N$ have a request of π_i, whereby the request of the depots and the recharge stations is equal to zero. Furthermore, each node has a predefined time window $[t_i^a, t_i^b]$. To fulfill the unloading operation or the recharging of a vehicle, each customer node is associated with a service time s_i ($i \in C$), and each recharge station with a service time s_h ($h \in R$).

The following decision variables are necessary to formulate the MIP Model for the EVRPTW-R-VC. To determine the route (including all possible visits to recharge stations) of each vehicle k, the binary variable x_{ijk} is introduced with $i,j \in N$ and $k \in K$. The variable x_{ijk} will be equal to one iff a vehicle travels along the arc $(i,j) \in A$. The variable x_{ijk} cannot be used in a similar way as it is usually used in VRP-like models for identifying the sequence of customer visits for each vehicle, since the recharge stations substantially differ from customer locations. In contrast to customer locations, a recharge station can be visited by a single vehicle once, several times or even not at all. Additionally, a recharge station is not exclusively assigned to one single vehicle since its service should be accessible for all vehicles; i.e. it can be visited by more than one vehicle. That is why a complex construction is needed for scheduling the customer visits for each vehicle. For this construction we introduce the binary variable z_{ijk}^h with $h \in R$, $i, j \in C \cup D$, $k \in K$. The sequence of customer visits of a vehicle k is represented by considering the term $\sum_{h \in R} z_{ijk}^h$. According to the sequence of customer services of vehicle k, $\sum_{h \in R} z_{ijk}^h = 1$ denotes that a customer j is the direct successor of a customer i; otherwise $\sum_{h \in R} z_{ijk}^h = 0$. This means that the above term has the same meaning as a binary variable x_{ijk} usually has in a VRP-like model for indicating that a vehicle directly travels on the link from i to j; except that for z_{ijk}^h the visit of a recharge station h is allowed in between.

Consequently, in our model, it is not possible that a vehicle visits on its way from a customer location to its direct successor two recharge stations; it can only visit one recharge station in between. However, the model below enables that a vehicle can come back to a recharge station as often as it seems to be advantageous; additionally, it can freely choose to visit any recharge station at any time, since we allow that several vehicles can use a recharge station simultaneously. The binary variable y_{jk} indicates whether vehicle $k \in K$ visits the customer node $j \in C$ ($y_{jk} = 1$) or not ($y_{jk} = 0$). Please note that x_{ijk} is defined on $N \times N$ while y_{jk} is defined on $C \times C$, only. To determine the payload that is transported by vehicle $k \in K$ from node $i \in N$ to node $j \in N$, the decision variable q_{ijk} is introduced. For a better understanding and in advance to the detailed presentation of the model of the EVRPTW-R-VC, we add some more explanations referring to the relationship between x_{ijk} and z^h_{ijk}. On its trip from $i \in C$ to the direct successor $j \in C$, it is allowed that a vehicle $k \in K$ travels to a recharge station $h' \in R$. As we will be see below, the binary variable $z^{h'}_{ijk}$ will be equal to one for this recharge station h'. If vehicle $k \in K$ serves customer node $j \in C$ directly after customer node $i \in C$ without making use of any recharge station, then it is meaningless for which recharge station $h \in R$ the binary variable z^h_{ijk} will be equal to one. However, there will be exactly one recharge station h with $z^h_{ijk} = 1$ since $\sum_{h \in R} z^h_{ijk}$ has to be equal to one. In other words, $\sum_{h \in R} z^h_{ijk} = 1$ opens up the possibility to visit a recharge station between two customers, but the decision which arc is used by vehicle $k \in K$ will be determined by the value of x_{ijk}.

The service at node $j \in C$ will start at w_j. To calculate the energy content of vehicle $k \in K$ before it leaves node $i \in N$ in direction $j \in N$, the decision variable e_{ijk} is implemented. The EVRPTW-R-VC is formalized by the model (2)– (30)

$$\min \sum_{i=0}^{n+1+r} \sum_{j=0}^{n+1+r} \sum_{k=1}^{m} d_{ij} \cdot (a_k \cdot x_{ijk} + b_k \cdot q_{ijk}) \tag{2}$$

subject to

$$\sum_{j=1}^{n+1} \sum_{h=n+2}^{n+1+r} z^h_{0jk} = 1 \quad \forall k \in K \tag{3}$$

$$\sum_{i=0, i \neq n+1}^{n+1+r} \sum_{h=n+2}^{n+1+r} z^h_{in+1k} = 1 \quad \forall k \in K \tag{4}$$

$$\sum_{i=0}^{n} \sum_{h=n+2}^{n+1+r} z^h_{ijk} - \sum_{i=1}^{n+1} \sum_{h=n+2}^{n+1+r} z^h_{jik} = 0 \quad \forall j \in N \setminus D, \forall k \in K \tag{5}$$

$$\sum_{i=0}^{n+1}\sum_{h=n+2}^{n+1+r} z_{ijk}^{h} = y_{jk} \quad \forall j \in C, \quad \forall k \in K \tag{6}$$

$$\sum_{k=1}^{m} y_{jk} = 1 \quad \forall j \in C \tag{7}$$

$$\sum_{j=0}^{n} \pi_j \cdot y_{jk} \le Q_k \quad \forall k \in K \tag{8}$$

$$x_{ijk} + \frac{1}{2}\cdot\left(x_{ihk} + x_{hjk}\right) \ge z_{ijk}^{h} \quad \forall i,j \in N \backslash R, h \in R, k \in K \tag{9}$$

$$\begin{aligned} & x_{ijk} + \sum_{h=n+2}^{n+1+r} \frac{1}{2}\cdot\left(x_{ihk} + x_{hjk}\right) - \\ & \qquad M \cdot \left(1 - \sum_{h=n+2}^{n+1+r} z_{ijk}^{h}\right) \le 1 \quad \forall i,j \in N \setminus R, \quad \forall k \in K \end{aligned} \tag{10}$$

$$w_i + s_i + t_{ij} - M \cdot (1 - z_{ijk}^{h}) \le w_j \quad \forall i,j \in N \setminus R, \quad \forall h \in R, \forall k \in K \tag{11}$$

$$\begin{aligned} & w_i + s_i + s_h + t_{ih} + t_{hj} - \\ & \qquad M \cdot (2 - z_{ijk}^{h} - x_{ihk}) \le w_j \quad \forall i,j \in N \setminus R, \forall h \in R, \quad \forall k \in K \end{aligned} \tag{12}$$

$$t_i^a \le w_i \le t_i^b \quad \forall i \in N \setminus R \tag{13}$$

$$x_{iik} = 0 \quad \forall i \in N, \forall k \in K \tag{14}$$

$$\sum_{i=0}^{n+1+r} q_{ijk} - \sum_{i=0}^{n+1+r} q_{jik} = \pi_j \cdot y_{jk} \quad \forall j \in N \setminus D, \forall k \in K \tag{15}$$

$$\begin{aligned} q_{ihk} + M \cdot \left(1 - z_{ijk}^{h}\right) \ge q_{hjk} \quad & \forall i \in N \setminus \{R \cup n+1\}, \\ & \forall j \in N \setminus \{R \cup 0\}, \\ & \forall h \in R, \forall k \in K \end{aligned} \tag{16}$$

$$\sum_{h=n+2}^{n+1+r} Q_k \cdot z_{ijk}^h \geq q_{ijk} \quad \forall i,j \in N \setminus R, \quad \forall k \in K \tag{17}$$

$$Q_k \cdot x_{ijk} \geq q_{ijk} \quad \forall i,j \in N, \quad \forall k \in K \tag{18}$$

$$\sum_{i=0}^{n+1+r} \sum_{j=0}^{n+1+r} d_{ij} \cdot x_{ijk} \leq T_k \quad \forall k \in K \tag{19}$$

$$\begin{aligned}&\sum_{i=0}^{n+1+r} e_{ijk} - \sum_{i=1}^{n+1+r} e_{jik} - \\ &\sum_{i=0}^{n+1+r} d_{ij} \cdot \left(a_k \cdot x_{ijk} + b_k \cdot q_{ijk}\right) = 0 \quad \forall j \in C, \forall k \in K\end{aligned} \tag{20}$$

$$d_{ij} \cdot \left(a_k \cdot x_{ijk} + b_k \cdot q_{ijk}\right) \leq e_{ijk} \quad \forall i,j \in N, \forall k \in K \tag{21}$$

$$E_k \cdot x_{0jk} = e_{0jk} \quad \forall j \in N, \quad \forall k \in K \tag{22}$$

$$0.8 \cdot E_k \cdot x_{hjk} = e_{hjk} \quad \forall h \in R, \quad \forall j \in N, \quad \forall k \in K \tag{23}$$

$$E_k \cdot x_{ijk} \geq e_{ijk} \quad \forall i,j \in N, \quad \forall k \in K \tag{24}$$

$$\sum_{h=n+2}^{n+1+r} E_k \cdot z_{ijk}^h \geq e_{ijk} \quad \forall i,j \in N \setminus R, \quad \forall k \in K \tag{25}$$

$$q_{ijk} \geq 0 \quad \forall i,j \in N, \forall k \in K \tag{26}$$

$$w_i \geq 0 \quad \forall i \in N \tag{27}$$

$$x_{ijk} \in \{0,1\} \quad \forall i,j \in N, \forall k \in K \tag{28}$$

$$z_{ijk}^h \in \{0,1\} \quad \forall i,j \in N, \forall h \in R, \forall k \in K \tag{29}$$

$$y_{ik} \in \{0,1\} \quad \forall i \in N, \forall k \in K \tag{30}$$

The objective function (2) minimizes the total amount of energy used. Constraints (3) to (7) are trivial equations usually used in the same way for modeling typical VRPs; except that in (3) to (7) the term $\sum_{h\in R} z_{ijk}^h$ is used instead of a binary variable x_{ijk}. Constraints (3) ensure that all vehicles will leave the starting depot; Constraints (4) guarantee that all vehicles will end their route at the duplicated ending depot $n+1$. If a vehicle travels to a node, it must leave this node as well (Eq. (5)). Each customer will be served exactly once by one vehicle due to Constraints (6) and (7). The total loading capacity of a vehicle $k \in K$ will not be exceeded (Constraints (8)). Constraints (9) and (10) specify the relationship between x_{ijk} and z_{ijk}^h. Due to Constraints (3) - (7), the decision variable z_{ijk}^h will be set to one for exactly one $h \in R$ if vehicle k serves customer i directly before j. Constraints (9) postulate that, if a vehicle k has customer j as direct successor of customer i in its route, then this vehicle k must go directly from node i to node j, or it must use a recharge station h. Moreover, Constraints (9) require that this vehicle k has to chose exactly that recharge station h' which has caused $\sum_{h\in R} z_{ijk}^h$ to become equal to one. To determine whether a vehicle travels in between to the recharge station h' or not, the sum of the decision variables $x_{ih'k}$ and $x_{h'jk}$ or alternatively x_{ijk} must be equal to one. Constraints (10) prohibit that vehicles do both, going the direct way from i to j and visiting a recharge station. The time windows are observed by Constraints (11)–(13). Constraints (11) refer to the case that no recharge station is used between the visits of customers i and j. In this case a formulation similar to the widespread Big M formulation for time windows within VRPs is used. Constraints (12) consider the situation that a recharge station is used between visiting customer i and j. In this case, which is equivalent to the fact that both variables z_{ijk}^h and x_{ijk} are equal to one, the time for traveling to and from the recharge station as well as the time for the recharging process itself have to be included in the Big M formulation for the time windows. The model does not set a service starting time at a recharge station. This allows to build subtours that are starting and ending at any of these recharge stations. Furthermore, a vehicle can visit a recharge station more than one time. Constraints (13) ensure that all nodes are visited during their predefined time windows. Constraints (14) forbid that x_{iik} becomes equal to one. Constraints (15) are responsible for balancing the flow of goods and for determining the quantity of goods that are transported between customer locations and/or recharge stations. Note that Eq. (15) are not sufficient for balancing the flow at recharge stations because only the sum of goods reaching a recharge station and the sum of goods leaving the recharge station are balanced. Equation (16) are needed additionally because a vehicle can visit a recharge station more than one time. If a vehicle visits a recharge station, the quantity of goods that is transported to this station must be equal to the quantity of goods that will be transported from this station. This requirement is ensured through Eq. (16) separately for each arrival at a recharge station. Constraints (17) and (18) are needed to prohibit that flows q_{ijk} will be installed on arcs which are never traversed by any vehicle. The maximal travel distance of a vehicle cannot be transcended (Eq. (19)). The energy consumption of a vehicle k on an arc (i, j) is represented by Constraints (20). Due to Constraints (21), (22), (23), (24) and (25) the decision variable e_{ijk} ranges between the required energy to travel along an arc (i, j) and the maximal provided energy E_k. Furthermore, the total energy content respectively 80% of the maximal energy content of a vehicle is available after leaving the depot respectively visiting a recharge station. Constraints (26) and (27) exclude negative payload and service starting times, respectively. The binary decision variables are set through Constraints (28)–(30).

The above MIP formulation is used for solving test instances in case of energy minimization. Additionally, we solve and compare the test instances in case of minimizing the total travel distance, which is equivalent to minimizing the total travel time and to minimizing the total drivers' working time without waiting time. In case of comparing times, the required time to travel over arcs, the time for service operations at customer nodes and the required time for recharge operations are summed in the objective function. Consequently, the following formulation (31) is used for travel time minimization.

$$\min \sum_{i=0}^{n+1+r} \sum_{j=0}^{n+1+r} \sum_{k=1}^{m} \left(t_{ij} + s_j\right) \cdot x_{ijk} \tag{31}$$

5 Computational study

In this section, a computational study is provided to analyze the utilization of CVs and EVs of different size and capacity. Therefore, specific instances with typical characteristics for urban and local rural transport are created. The optimal transportation plans of these instances are generated by solving the MIP model from Sect. 4 using the commercial solver IBM ILOG CPLEX 12.6.1. CPLEX is run on a computer with an Intel(R) Core(TM) i7-6500U CPU, 8GB random access memory and a Windows 10 operating system.

5.1 General construction of test cases

The general setting that is valid for the computational study is as follows. First, we have generated 10 different generic problem instances with ten customer nodes. The zone of interest of all instances has a size of 50 × 50 km; in other words, all relevant locations are positioned in the square [0, 50] × [0, 50]. One depot is maintained and located at the middle of the square (at the coordinates (25, 25) for the generic instances). The customer locations are randomly scattered in the square. Each customer node has a randomly generated demand that varies within the interval $]0to, 3to]$. The time windows of the customer nodes $i \in C$ are randomly generated within the interval $[t_{0i}, 500 - t_{in+1} - s_i]$ and have a duration of 10 min. The time window of the depot is set open. The service time at a customer node is defined to be 15 min. Then, based on the initial set of 10 generic problem instances, specific test cases are generated by variations.

The first type of variation is provided by considering vehicles of different size and powering. There are four vehicle types, as shown in Table 2. For each of these vehicle types, we consider one homogeneous fleet. Each homogeneous vehicle fleet consists of 10 vehicles of its specific type. Additionally, a heterogeneous fleet is considered. Since we want to investigate the maximal potential of mixed fleets, we ensure that there is no lack of vehicles of any type when the heterogeneous fleet is used; therefore, the heterogeneous vehicle fleet consists of 10 vehicles of each vehicle type. In other words, we assume an ideal heterogeneous fleet whose potential for vehicle routing allows the generation of a reference value for mixed fleets that can only be achieved by other heterogeneous fleets for a given problem instance if the number of available vehicles of any type does not become restrictive for solving the given instance. We admit that carriers cannot change the composition of their fleet from day to day. However, carriers may approximate the reference value of the ideal fleet by operating a fleet that is well adapted to their own order situation. Additionally, carriers can improve the conformity of the used vehicle types by subcontracting a portion of their transportation requests (Wang et al. 2014). In the following, a homogeneous fleet with EVs of type *EV*(7.5) and *EV*(18) is denoted as *E-HOM*(7.5) and *E-HOM*(18), respectively. Analogously, a homogeneous fleet with CVs of size 7.5 tons and 18 tons is denoted as *C-HOM*(7.5) and *C-HOM*(18), respectively. The heterogeneous fleet composed of all the above vehicle types is called *HET*.

The second type of variation for generating test cases is provided by scaling the square of relevant locations by a gauge factor g ($g = 1, 2, 3,$ or 4). Scaling the square means that the side length SL of the square is stretched by the gauge factor. The depot remains in the middle of the square. All distances from the depot to relevant locations (i.e. customer locations and recharge stations) are also stretched by the gauge factor. Of course, the distances between all locations are consistently stretched, too. The distance from the depot to a customer location is denoted as costumer distance. Since the distance from the depot to a location in the corner of the square is $1/2 \cdot SL \cdot \sqrt{2}$, the maximal customer distance amounts to 35, 70, 105 and 140 km for $g = 1, 2, 3,$ and 4, respectively.

In addition to the above variations for generating test cases, the option of including recharge stations is considered. The time windows of the recharge stations are set open; and the time for recharging is set to 60 min. The demand π_h, $h \in R$, is equal to zero. The recharge stations are located within the considered square, but they should not be located close to the depot; therefore, they are required to be located outside of an inner circle that identifies the prohibited area for recharge stations. The center of the inner circle is provided by the depot, and its radius is equal to half of the side length of the original square. Furthermore, the effect of an augmentation of the battery-size of EVs is analyzed.

Two different objective functions are considered: energy minimization (Scenario E) and travel time minimization (Scenario T). For energy minimization, the objective function (2) from Sect. 4 is used. For travel time minimization, the objective function (31) is used. The assignment of vehicle types to the time-optimal routes of Scenario T is determined by choosing for each route the most energy efficient vehicle type out of all feasible types (with respect to the driving range and the capacity). The computational experiments are based on the vehicle characteristics shown in Tables 2 and 3. Five different vehicle fleets are investigated: the homogeneous fleets *E-HOM*(7.5), *E-HOM*(18), *C-HOM*(7.5), and *C-HOM*(18) as well as the heterogeneous fleet *HET* composed of these four homogeneous fleets.

Nongeneric (i.e. real) test cases are generated by considering the 10 generic test instances for each gauge factor ($g = 1, 2, 3$, and 4) and each of the five different fleets. The set of 10 test cases for a fixed value of g and a specific fleet is denoted as test-set (g, F). Altogether, there are 200 test cases for each Scenario E and T.

5.2 Instances without recharge stations

In this section, test cases without the option of recharging EVs are considered. All 400 test cases (for Scenario T and E together) could be solved to optimality within an average computation time of 2.4 s for Scenario T and 5.5 s for Scenario E. Table 4 shows the portions of different types of vehicles used by the heterogeneous fleet *HET* in case of Scenario T. The first column (V_{total}) denotes the number of overall used vehicles; and the next four columns show the numbers of vehicles used for each single vehicle type contained in *HET*. For both Scenarios T and E, it can be observed that all available vehicle types come into operation for request fulfillment by *HET* for any value of g. Furthermore, it can be seen that the number of totally used vehicles decreases if the customer distances increase; concurrently, the portion of EVs decreases, whereas the portion of used CVs increases. This might be caused by the fact that, for longer customer distances, it is profitable to make use of the CVs' ability to execute large tours with more customers, while for test instances with shorter customer distances, it is more beneficial to generate smaller tours which are fulfilled by additional energy-efficient vehicles. *EV*(18) is the most used vehicle type in Scenario T (Table 5). This shows that, on the one hand, the aggregated customer demand and tour length of most travel time-optimal routes are too high for vehicles with 7.5 tons gross weight, while on the other hand, vehicles of type *EV*(18) are sufficient (with respect to the driving range (maximal 300 km for an empty vehicle) and payload (maximal 6 tons)) to fulfill most of the generated travel time-optimal routes. In Scenario E (Table 7), however, vehicles of type *EV*(18) are hardly used and replaced by vehicles of types *EV*(7.5) and *CV*(7.5), since the smaller vehicles are more energy efficient than the vehicles of type *EV*(18).

For homogeneous fleets, the number of used vehicles is shown in Tables 5 and 8. Since the driving range of an *EV*(7.5) is limited to 130 km, it can only be warranted for $g = 1$ (i.e. a maximum customer distance of 35 km) that all test cases are feasible for *E-HOM*(7.5). For all other fleets, there is no infeasibility, since the driving range is sufficient to install a pendulum tour from the depot to any customer location

Table 4 Scenario T: number of used vehicles of heterogeneous fleet *HET*

g	V (*total*)	*EV*(7.5)	*EV*(18)	*CV*(7.5)	*CV*(18)
1	3.5	1.5	1.2	0.3	0.5
2	3.4	0.7	1.0	1.0	0.7
3	3.3	0.5	0.9	1.1	0.8
4	3.2	0.2	0.8	1.2	1.0

Table 5 Scenario T: number of used vehicles of homogeneous fleets

g	*EV*(7.5)	*EV*(18)	*CV*(7.5)	*CV*(18)
1	5.3	3.8	4.5	3.5
2	6.1 (7)	3.8	4.5	3.4
3	– (0)	3.7	4.5	3.3
4	– (0)	4.1	4.6	3.2

for any value of g. For $g > 1$ and *E-HOM*(7.5), the number of feasible test cases is shown in brackets.

Similar to *HET*, the number of CVs used in *C-HOM*(18) decreases, and the number of EVs used in *E-HOM*(18) increases when the customer distances increase. *C-HOM*(7.5) needs more vehicles than *E-HOM*(18), although the driving range of vehicles from *C-HOM*(7.5) is larger. In this case, the higher payload of *E-HOM*(18) is decisive.

The rows “Time”, respectively “Energy” in Table 6 denote the total travel times of the routes of the optimal solutions respectively the amount of energy needed for fulfilling these routes.

Scenario T applies the same objective function (travel time minimization) for all vehicle types. Consequently, it is always beneficial to choose a fleet composed of vehicles with a high potential (with respect to both driving range and loading capacity) for transportation planning. That is why, the travel time-optimal values in Table 6 are equal for *C-HOM*(18) and *HET*. In all other cases, fleets with vehicles of less potential lead to a ranking with more or less substantially worse optimal values for the travel time. Refer to Table 6 for a comparison of the optimal values of the travel times. If $g = 1$, all relevant locations are near (below 35 km) the depot; in this case, using *E-HOM*(7.5) leads to the longest travel times (i.e. worst objective value) but the lowest energy consumption, compared with all other homogeneous fleets.

Especially, the comparison of the two fleets *C-HOM*(7.5) and *E-HOM*(18) with diverging capabilities (with respect to driving range and payload) might be suspenseful. It can be seen that (for Scenario T averaged over all values of g) the optimal values for the total travel time for *E-HOM*(18) are 11% better than for *C-HOM*(7.5).

Table 6 Scenario T: values for minimal travel time and resulting energy consumption

g		*HET*	*E-HOM* (7.5)	*E-HOM* (18)	*C-HOM* (7.5)	*C-HOM* (18)
1	**Time**	**367.93**	**426.60**	**373.45**	**404.33**	**367.93**
	Energy	1516.49	1371.96	1831.27	1608.60	1869.11
2	**Time**	**575.42**	–	**591.81**	**654.21**	**575.42**
	Energy	3165.59	–	3626.05	3194.39	3666.33
3	**Time**	**783.25**	–	**808.13**	**903.19**	**783.25**
	Energy	4804.47	–	5404.22	4771.79	5470.31
4	**Time**	**985.52**	–	**1074.10**	**1155.54**	**985.52**
	Energy	6397.89	–	7549.22	6345.26	7212.95

Table 7 Scenario E: number of used vehicles of heterogeneous fleet *HET*

g	$V(total)$	$EV(7.5)$	$EV(18)$	$CV(7.5)$	$CV(18)$
1	4.9	4.2	0.0	0.4	0.3
2	5.0	3.5	0.0	1.0	0.5
3	4.7	1.8	0.1	2.4	0.4
4	4.1	0.8	0.3	2.5	0.5

Table 8 Scenario E: number of used vehicles of homogeneous fleets

g	$EV(7.5)$	$EV(18)$	$CV(7.5)$	$CV(18)$
1	5.5	3.8	4.8	3.6
2	6.3 (7)	3.9	4.8	3.5
3	– (0)	3.8	4.7	3.4
4	– (0)	4.2	4.7	3.2

This result is caused by the higher payload of *E-HOM*(18). However, Table 6 shows that the fleet *C-HOM*(7.5) is surprisingly more energy efficient for time-optimal routes than any other homogeneous fleet (except *E-HOM*(7.5) for $g = 1$; see above). In particular, *C-HOM*(7.5) needs 18% less energy than *E-HOM*(18). This result shows that vehicles of type *CV*(7.5) can take advantage of their low dead weight. For vehicle routing problems, most planners apply (working-) time minimization because they believe minimizing their transportation costs in this way. Consequently, for the criterion that is primarily applied in practice (time), *C-HOM*(7.5) is by far the most energy efficient homogeneous fleet in typical field applications for mid-sized cargo on short and medium travel distances.

It may also be interesting to compare the two vehicles with the identical gross weight of 18 tons for Scenario T. Averaged over all values of g, *C-HOM*(18) is 6% less time consuming than *E-HOM*(18). With respect to energy consumption, *E-HOM*(18) performs better for short customer distances ($g = 1$ and $g = 2$), while *C-HOM*(18) performs better for longer customer distances ($g = 3$ and $g = 4$). However, it is, surprising that, not only in terms of travel time but also in terms of energy consumption, *C-HOM*(18) is, on average, slightly superior (by 1%) to the *E-HOM*(18). This result is caused by the large driving range and the high loading capacity of *C-HOM*(18), which enable a more efficient bundling with a reduced number of required vehicles, mainly for $g = 4$.

Tables 7, 8 and 9 show the computational results for Scenario E. Since the objective function of Scenario E is composed of different vehicle-specific terms for the energy consumption of different types of vehicles, the effect of choosing fleets with more powerful vehicles (with respect to range and payload) cannot be predicted simply. Nevertheless, as a matter of course, the best values of the objective function will definitively always be achieved for *HET*, since *HET* comprises all other vehicle types; consequently, each solution for any homogeneous fleet is also contained in the solution space of *HET*. The computational experiments performed for Scenario E are shown in Table 9. The results of these experiments demonstrate that

Table 9 Scenario E: values for minimal energy consumption and resulting travel time

g		*HET*	*E-HOM* (7.5)	*E-HOM* (18)	*C-HOM* (7.5)	*C-HOM* (18)
1	Time	401.88	427.38	373.45	404.78	368.17
	Energy	**1344.33**	**1369.66**	**1831.27**	**1602.18**	**1864.23**
2	Time	640.68	–	591.82	655.21	575.90
	Energy	**2824.38**	–	**3623.89**	**3183.44**	**3656.56**
3	Time	855.21	–	808.14	904.54	783.96
	Energy	**4484.59**	–	**5400.98**	**4754.34**	**5455.65**
4	Time	1046.55	–	1074.64	1156.06	985.52
	Energy	**6038.35**	–	**7541.96**	**6339.13**	**7212.95**

Table 10 Scenario E vs. Scenario T: relative difference ((E-T)/T) of characteristic values

Fleet	Vehicle (%)	Time (%)	Energy (%)
HET	39.55	8.56	– 7.51
E-HOM(7.5)	3.77	0.18	– 0.17
E-HOM(18)	1.95	0.02	– 0.07
C-HOM(7.5)	4.97	0.11	– 0.26
C-HOM(18)	2.24	0.05	– 0.16

the superiority of *HET* compared with heterogeneous fleets is greater than that for Scenario T. *HET* outperforms *E-HOM*(7.5) (for its solely applicable value of the gauge factor $g = 1$) not only with respect to energy (which is self-evident since this is the objective function) but also with respect to travel time. *HET* also outperforms *C-HOM*(7.5) with respect to both energy consumptions and travel time. It further turns out that the ranking of homogeneous fleets for Scenario E is the same as for Scenario T. Averaged on all values of g, *HET* needs 7.48, 19.23 and 20.15% less energy than *C-HOM*(7.5), *C-HOM*(18), and *E-HOM*(18), respectively. Considering homogeneous fleets only, it can be seen that *E-HOM*(7.5) is the most energy efficient fleet for $g = 1$ in Scenario E. For all other values of g, *C-HOM*(7.5) has turned out to be the most energy efficient homogeneous fleet.

Surprisingly, for $g = 3$ and $g = 4$ the amount of energy consumed by *C-HOM*(7.5) in Scenario E is less than the amount of energy used by *HET* in Scenario T. This makes the use of *C-HOM*(7.5) in energy minimized routes an attractive alternative to using *HET* in travel time minimized routes, provided that the customer demands are below 3 tons and customer locations are located between 70 and 140 km away from the depot.

Additionally, we performed experiments on a truck-trailer combination consisting of a *CV*(18) and a trailer of 18 tons gross weight. However, in case of adding such a truck-trailer combination as a fifth vehicle type to the heterogeneous fleet, this vehicle type is not used in Scenario E. Furthermore, the travel times of optimal solutions are identical for Scenario T and Scenario E. Finally, the minimal travel times of the truck-trailer combination are nearly equal to the values obtained for *C-HOM*(18) in Scenario T. In sum, we observe that the truck-trailer combination cannot exploit its advantage of having a high capacity. It is simply too large for such small customer demands and such short customer distances as considered in our test cases.

Tables 6 and 9 demonstrate that the objective values of the optimal solutions are not exactly proportional to the value of the gauge factor. In Table 6, the travel times deviate for *E-HOM*(18) by – 1, + 3, + 3% from the proportional values for $g = 2$, $g = 3$, $g = 4$, respectively. For *C-HOM*(7.5) the deviations are – 1, – 1, – 1%, and for *C-HOM*(18) the values are – 2, – 3, – 3%, respectively. In general, the increase of travel times for *E-HOM*(18) tends to values that are slightly higher than proportional in relation to the growth of the customer distances, whereas the increase for homogeneous fleets with CVs is less than proportional.

To compare the energy versus travel time minimization, the relative deviations of Scenario E to Scenario T (i.e.((E-T)/T)) are presented in Table 10 for the number of used vehicles, the total travel time and the amounts of energy used. Table 10 shows that the values derived for Scenario T and Scenario E are similar unless *HET* is used. For *HET*, the potential for energy reduction is tremendous if Scenario E instead of Scenario T is considered. This finding is consistent with the insights derived from the existing research on green vehicle routing for heterogeneous fleets (see e.g. (Kopfer et al., 2014)).

5.3 Variation of the battery size

Recently, the market for commercial vehicles has been providing flexibility with respect to the energy capacity of EVs. In particular, trucks with modular battery systems are offered (oV 2015, 2016). These modular battery systems consist of one, two or more identical batteries installed in an electric powered truck.

To vary the characteristics of the EVs considered in Sect. 3, an alternative type of EVs with a gross weight of 7.5 tons and an alternative type of EVs with 18 tons gross weight are introduced. While vehicles of type *EV*(7.5) and *EV*(18) are standard vehicles equipped with normal battery size, the vehicles of the alternative types (denoted as *DEV*(7.5) and *DEV*(18), respectively) are equipped with a modular system containing more battery capacity. This results in a nearly doubled battery capacity for *DEV*(7.5) and a 50% higher battery capacity for *DEV*(18). A homogeneous fleet consisting of vehicles of type *DEV*(7.5) respectively *DEV*(18) is denoted as *DE-HOM*(7.5) respectively *DE-HOM*(18).

The maximum driving range of a *DEV*(7.5) is drastically increased to 250 km, in comparison to 130 km for an *EV*(7.5); the range of a *DEV*(18) is increased to 430 km compared to 300 km for an *EV*(18). However, the maximal payload is reduced for both vehicle types due to the weight of the additional battery.

Table 11 Characteristics and parameters of *DEV*(7.5) and *DEV*(18)

	Empty weight [*to*]	Payload [*to*]	a_k [$\frac{MJ}{km}$]	b_k [$\frac{MJ}{tkm}$]	E_k [MJ]
DEV(7.5)	4.5	3.0	4.531	0.5266	1086
DEV(18)	13.2	4.8	8.051	0.2425	3492

Table 12 Scenarios T and E: relative deviation to *E-HOM*(18) and *HET* caused by battery augmentation

g	Scenario T		Scenario E	
	E-HOM(18) (%)	*HET* (%)	*E-HOM*(18) (%)	*HET* (%)
1	3.49	0.27	9.00	0.00
2	4.49	0.35	9.30	0.00
3	5.12	0.39	9.51	0.02
4	0.82	0.41	4.56	0.36

Table 13 Scenario E: relative deviations from *C-HOM*(7.5)

g	*C-HOM*(7.5) (%)	*E-HOM*(7.5) (%)	*DE-HOM*(7.5) (%)	*C-HOM*(18) (%)	*E-HOM*(18) (%)	*DE-HOM*(18) (%)
1	0.00	– 14.51	– 4.40	16.36	14.30	24.59
2	0.00	–	– 3.77	14.86	13.84	24.42
3	0.00	–	– 0.94	14.75	13.60	24.40
4	0.00	–	–	13.78	18.97	24.40
Ø	0.00	–	–	14.55	15.86	24.43

Table 11 shows the relevant characteristics of vehicles of type *DEV*(7.5) and type *DEV*(18).

In this section, the effect of augmenting the battery size of EVs is analyzed. All test cases for $g = 1$, 2, and 3 become feasible for *DE-HOM*(7.5), since the driving range of a *DEV*(7.5) is sufficient to realize pendulum tours for test sets with $g = 3$; i.e. with a maximal customer distance to a maximum of 105 km. The computational experiments have shown that two test cases were even feasible for $g = 4$. A comparison between *DE-HOM*(7.5) and *E-HOM*(7.5) is only possible for $g = 1$, since for other values of g, the test cases are infeasible for *E-HOM*(7.5). For $g = 1$, the augmentation of the battery capacity worsens the results for Scenario T; specifically, the value of the objective function (needed total travel time) is 5.6% higher than for *EV*(7.5), while the amount of energy used also increases. For Scenario E, the comparison shows that *DE-HOM*(7.5) needs 12% more energy than *E-HOM*(7.5) for $g = 1$. Compared to *C-HOM*(7.5), however, *DEV*(7.5) needs 2.5% less energy averaged on $g = 1, 2$, and 3. The optimal values of *HET* nearly remain unchanged (+ 0.3% for Scenario T and −0.3% for Scenario E) if vehicles of type *EV*(7.5) are replaced by vehicles of type *DEV*(7.5).

The effects of augmenting the battery size of EVs with 18 tons gross weight is considered for Scenarios T and E.

Table 12 shows the relative difference of the optimal objective values achieved for *DE-HOM*(18) compared to the optimal values for *E-HOM*(18) (i.e. (*DE-HOM* – *E-HOM*) / *E-HOM*) for both scenarios. Furthermore, the relative difference for replacing *E-HOM*(18) by *DE-HOM*(18) in *HET* is shown. It turns out that all values are positive; in other words, the objective values obtained for

Scenarios T and E could not be improved for any test set. This finding shows that the battery capacity of vehicles of type *EV*(18) is well-suited for field applications with customer demands below 3 tons and customer distances as much as 140 km. Since the vehicle characteristics in Table 2 are taken from the attributes of real EVs, which constitute standard types in the market for commercial vehicles, this result affirms that the 18 ton-EVs offered by the market are well-configured for medium- and short-distance cargo.

Table 13 summarizes the results obtained for the experiments which have been performed on test cases without recharge stations. This table uses the energy consumption of *C-HOM*(7.5) as the reference value and, for all other homogeneous fleets, shows the relative difference of their energy consumption to the amount of energy consumed by *C-HOM*(7.5). For Scenario T, the results are similar since the deviations between Scenarios E and T are only small for homogeneous fleets (cf. Table 10). To obtain meaningful entries for a mixed fleet in Table 13, *HET* should be extended by including *DE-HOM*(7.5) and *DE-HOM*(18). The test sets for the extended heterogeneous fleet are not considered in Table 13 since solving the test cases of these test sets is very time consuming. However, it is self-evident that the extended heterogeneous fleet would outperform each homogeneous fleet in Table 13.

5.4 Instances with recharge stations

The option of recharging vehicle batteries en route extends the driving range of EVs; thus, the solution space for routing a fleet consisting of EVs is enlarged. Consequently, some of the infeasible test cases of Scenario T and Scenario E may become feasible. First, we modify the planning situation of the test cases analyzed in Sect. 5.2 by providing randomly located recharge stations. Therefore, we modify each planning situation five times; in other words, we randomly generate 5 coordinates for the first and 5 coordinates for the second recharge station and include one respectively two of them into the instances. For our analysis, we have utilized the average of the 5 solutions obtained for each scenario. Expanding Scenario T respectively Scenario E by the existence of one recharge station yields Scenario T-1 respectively Scenario E-1. Extending T respectively E by two recharge stations yields Scenario T-2 respectively Scenario E-2. Second, we add four recharge stations to the planning situation described by the generic problem instances. The recharge stations of the generic instances are located at the coordinates (10, 10), (10, 40), (40, 10) and (40, 40). For test cases with $g > 1$, the positions of the recharge stations are consistently adjusted to the scaling of the square of relevant locations. The positions and arrangement of the recharge stations guarantee that all test cases will be feasible for *E-HOM*(7.5) so long as $g \leq 3$. Scenarios extended by four recharge stations are denoted as T-4 and E-4, respectively. The additional time for recharging is considered in scenarios with recharge stations.

In a first computational study, the scenarios with randomly located recharge stations (i.e. T-1, E-1, T-2, and E-2) are analyzed. For Scenarios T-1 and E-1, all test cases could be solved to optimality without any gap. The average computation time for solving the test cases of T-1 amounts to 27.6 s (compared to 2.4 s for Scenario T). The average computation time for Scenario E-1 is even higher. It amounts to 45.2 s. The existence of one randomly located research station only has the following effects. In 2 of 5 planning situations, all test cases become feasible for test-set (2, *E-HOM*(7.5)). For these feasible test sets, a comparison of *E-HOM*(7.5) with *C-HOM*(7.5) shows that *C-HOM*(7.5) averagely needs 1.8 vehicles less and 19.3% less time. However, *E-HOM*(7.5) needs 7.8% less energy than *C-HOM*(7.5).

For Scenarios T-2 and E-2 the maximal computation time was set to 3 h. The average computation time for Scenario T-2 amounts to 839.0 s; and all test cases can be solved to optimality. For Scenario E-2 the average computation time increases to 1034.6 s; and there are the following optimality gaps. For *DE-HOM*(7.5) and *DE-HOM*(18) one test set with $g = 3$ exhibits an optimality gap of 0.07% and 0.02%, respectively (averaged on all generic problem instances). For *HET*, 32 of 40 test cases have been solved to optimality. The test-sets with optimality gaps exhibit gaps of 0.03, 0.81 and 0.35% for $g = 1$, 2, and 3, respectively.

Adding a second randomly located recharge station has the following effects. For *E-HOM*(7.5), in 2 of 5 planning situations all test cases become feasible for the test-set with $g = 2$. Comparing E-2 with E-1, on average, a reduction of 0.1 vehicles, 1.2% energy, and 0.3% time is achieved. Only *HET* and *E-HOM*(7.5) slightly benefit from the option to use two recharge stations. The travel time cannot be reduced by providing a second recharge station; and the total energy consumption can only be reduced for three test cases by less than 0.5%. In case of T-2, the values of the objective function of the solutions obtained for one recharge station cannot be improved for any test case. Obviously, the time lost by recharging cannot be compensated by the enlarged driving range and more efficient routing of EVs which might be enabled by the second recharge station.

Table 14 summarizes the comparison of Scenario E-1 and E-2 with Scenario E; i.e. it demonstrates the benefits possibly achieved by adding recharge stations to the generic problem instances. In particular, for characteristic values of the optimal solutions obtained for Scenarios E-1 and E-2, Table 14 shows the average relative differences to the values obtained for Scenario E. The values in Table 14 are averaged for all values of g and for all test sets with differently located recharge stations. Homogeneous fleets with CVs are not included in Table 14, since they have no need for and no benefit from refueling. For *E-HOM*(7.5), only the results of the feasible

Table 14 Scenario E-1 and E-2: relative deviation to Scenario E

Fleet	One recharge station (E-1)				Two recharge station (E-2)			
	Vehicle (%)	RS	Time (%)	Energy (%)	Vehicle (%)	RS	Time (%)	Energy (%)
HET	0.21	+ 0.26	2.62	– 0.64	0.64	+ 0.53	5.47	– 1.32
E-HOM(7.5)	0.00	+ 0.00	0.00	0.00	0.00	+ 0.00	0.00	0.00
E-HOM(18)	– 1.02	+ 0.09	0.24	– 0.57	– 1.53	+ 0.12	0.33	– 0.69
DE-HOM(7.5)	– 0.92	+ 0.48	0.17	– 0.32	– 1.22	+ 0.45	0.20	– 0.43
DE-HOM(18)	0.00	+ 0.01	0.03	0.00	0.00	+ 0.01	0.03	0.00

test cases are compared with each other. In sum, the conclusion is that the randomly located recharge stations are seldom used. Using these stations only has a small positive effect on the objective function.

For Scenarios T-4 and E-4, the maximal computation time was also set to 3 h. Except for five test cases of test set (4, *E-HOM*(7.5)), all test cases are feasible. All feasible test cases could successfully be solved but none of the test sets could be solved without optimization gap. Solving Scenario E-4 for *HET*, *E-HOM*(7.5), and *E-HOM*(18) yields an optimization gap of averagely 8.9, 7.7 and 3.0%, respectively. Nevertheless, the relative improvement (i.e. deviation of Scenario E-4 to Scenario E) achieved for *HET*, *E-HOM*(7.5), and *E-HOM*(18) amounts to 3.0, 0.0 and 1.2%, respectively. The homogeneous fleet *E-HOM*(7.5) does not achieve any improvement since for this fleet the comparison of the scenarios is only possible for $g = 1$. It turned out that none of the fleets made use of a recharge station for $g = 1$. For $g = 2$ and $g = 3$, however, *E-HOM*(7.5) frequently uses recharge stations and even is superior to *DE-HOM*(7.5), which is the most energy efficient homogeneous fleet for $g = 2$ and $g = 3$ in Scenario E. Actually, using *E-HOM*(7.5) in Scenario E-4 outperforms the reference values of *C-HOM*(7.5) in Scenario E (cf. Table 13) by 11.9% for $g = 2$ and 5.7% for $g = 3$. However, using *E-HOM*(7.5) with the option of four recharge stations is by far the least time-efficient fulfillment mode; it needs 41% more time (for $g = 3$) and 70% more time (for $g = 4$) than *E-HOM*(18) without the option of recharging. Consequently, the energy costs decrease, while the labor costs of routes drastically increase due to the drivers' time spent on tour fulfillment. An analysis of EVs and CVs with respect to their total costs composed of cost factors such as energy costs and labor cost can be found in Goeke and Schneider (2015).

The outcome of the first computational study for including recharge stations has shown that the test cases of Scenarios T-2, E-2, and E-4 could not be solved to optimality. In order to get more reliable data through a second computational study, Scenario E-4 is considered for test cases with 8 customer locations; in other words, the 10 generic problem instances from Sect. 5.1 are reduced from ten randomly located customers to eight randomly located customers.

In case of eight customers, all feasible test cases for *E-HOM*(7.5) and *E-HOM*(18) can be solved to optimality within 16 minutes, on average. Only four test cases of (4, *E-HOM*(7.5)) are infeasible. The experiments for *HET* yield an optimality gap of 3.1% and a computation time of almost 2 h, on average. The relative improvement achieved by inserting four recharge stations amounts to 3.4, 0.0 and 1.2%, for *HET*, *E-HOM*(7.5), and *E-HOM*(18), respectively; i.e., the results are similar to those obtained for Scenario E-4 with ten customers. Similar to the test cases with ten customers, recharge stations have no effect for $g = 1$; they are only used in one single test case. Like in case of ten customers, *E-HOM*(7.5) frequently uses recharge stations, especially for $g = 2$ and $g = 3$. Due to the availability of four recharge stations, which are nearly perfectly located, *E-HOM*(7.5) is the most energy efficient homogeneous fleet for $g = 1, 2$, and 3. However, using *E-HOM*(7.5) in Scenario E-4 is by far more time consuming than using any other fleet in any other Scenario.

5.5 Configuration of efficient fleets

This section concentrates on scenarios without recharge stations and on the ranking of all homogeneous fleets introduced within these scenarios. Furthermore, the efficiency of the homogeneous fleets is set in relation to *HET* (as introduced in Sect. 5.2) and to two newly introduced heterogeneous fleets with a realistic number of available vehicles. Scenario T applies the same objective function (travel time minimization) to all vehicle types; therefore, the ranking of fleets considering the time efficiency only depends on the differences between the fleets with respect to their solution space. Let *SP*(*F*) denote the solution space for routing vehicles of a fleet *F*. Due to a greater driving range and a higher vehicle capacity, it holds that *SP*(*HET*) > *SP*(*C-HOM*(18)) > *SP*(*E-HOM*(18)) > *SP*(*E-HOM*(7.5)) and *SP*(*C-HOM*(18)) > *SP*(*C-HOM*(7.5)) > *SP*(*E-HOM*(7.5)). The only fleets with overlapping solution spaces are *E-HOM*(18) and *C-HOM*(7.5). The quality of the optimal solutions for Scenario T will always be ranked according to the above relations for the size of the fleets. Furthermore, replacing a vehicle of a given fleet by another vehicle with more potential will increase the solution quality. Moreover, adding a vehicle to a homogeneous fleet or extending a heterogeneous fleet by an additional vehicle type will also increase the solution quality. Things are more complicated for Scenario E since the objective function for energy minimization is composed of different terms for different vehicle types. Predicting the ranking of fleets or even finding a fleet which outperforms all other fleets (with respect to some given criterion) is a very challenging task for Scenario E.

All heterogeneous fleets considered in Sects. 5.2 and 5.3 are ideal fleets with 10 vehicles for each of their vehicle types. In this section, heterogeneous fleets with a reasonable number of vehicles are considered. The experiments in Sect. 5.2 have shown that six vehicles are sufficient to guarantee the feasibility of nearly all test cases. That is why we investigate heterogeneous fleets which are composed of six vehicles, maybe EVs or CVs. There are $\frac{11!}{5! \cdot 6!}$ (= 462) possibilities of building heterogeneous fleets with six vehicles. Based on the results from Sect. 5.2 and based on additional experiments on seeking attractive fleets, two supremely attractive fleets called *HET-A* and *HET-B* have been identified. *HET-A* consists of four vehicles of type *EV*(7.5) and two vehicles of type *CV*(18). *HET-B* is composed of one vehicle of type *EV*(7.5), one vehicle of type *DEV*(7.5), three vehicles of type *CV*(7.5) and one vehicle of type *CV*(18). Tables 15 and 16 show the results for the generic problem instances with ten customers (as in Sects. 5.2 and 5.3). The tables compare the efficiency of different fleets by showing their relative difference to *HET* as introduced in Sect. 5.2. First, the tables show that *HET-A* is very attractive for the test sets with short customer distances to a maximum of 35 km ($g = 1$). *HET-A* outperforms all other fleets considered for these test sets in travel time and energy minimization. Second, for test sets with longer customer distances ($g = 2$, 3, and 4), *HET-B* is the most attractive fleet in Tables 15 and 16; it outperforms all other fleets for these test sets.

Table 15 Scenario T: relative deviations from *HET*

g	*HET-A* (%)	*HET-B* (%)	*E-HOM*(7.5) (%)	*DE-HOM*(7.5) (%)	*E-HOM*(18) (%)	*DE-HOM*(18) (%)	*C-HOM*(7.5) (%)	*C-HOM*(18) (%)
1	0.88	2.95	15.95	22.50	1.50	5.05	9.89	0.00
2	2.63	4.14	–	30.59	2.85	7.47	13.69	0.00
3	–	4.79	–	38.10	3.18	8.45	15.31	0.00
4	–	5.79	–	–	8.99	9.88	17.25	0.00

6 Conclusions

In this study, fleets composed of EVs and CVs with a gross weight of 7.5 tons and 18 tons have been analyzed and compared in planning situations with small and medium-sized cargo and customer distances to a maximum of 140 km. This study concentrates primarily analyzes planning situations without recharge stations. For short customer distances to a maximum of 35 km, *E-HOM*(7.5) is the most energy efficient but most time consuming homogenous fleet. For customer distances above 35 km, this fleet can only be operated by accepting that recharging will be necessary and that, otherwise, only a small portion of the test cases are feasible. Additionally, the number of vehicles used as well as the total travel time increase drastically for distances above 35 km. For customer distances between 35 km and 105 km *DE-HOM*(7.5) is the most energy efficient fleet. *C-HOM*(7.5) is by far (more than 13% better than other homogeneous fleets) the most energy efficient homogeneous fleet for customer distances above 105 km, in both the energy minimization and travel time minimization scenarios. With respect to travel time and in case of Scenario T, size (i.e. payload) is the all-dominant factor. Specifically, *C-HOM*(18) is 6% superior to *E-HOM*(18), which, in turn, is 11% superior to *C-HOM*(7.5). However, in case of energy minimization the performance indicators for fleets with EVs and CVs of 18 tons gross weight are nearly equal. EVs are better for customer distances as high as 105 km, while CVs are better for distances above 105 km.

There is a positive effect of introducing one randomly located recharge station but it is rather small. First, the usability of small EVs with 7.5 tons gross weight is improved. However, only a subset of test cases with customer distances between 35 and 70 km become feasible for *E-HOM*(7.5). Second, EVs with 18 tons gross weight occasionally employ a recharge station but do so only for test cases with long customer distances to a maximum of 140 km. In this case, the energy consumption of *E-HOM*(18) can be reduced by 2%. Adding a second recharge station again slightly improves the usability of EVs with 7.5 tons gross weight. In sum, however, there is no significant positive effect on the energy efficiency of the homogeneous fleets.

Augmenting the battery size for vehicles of type *EV*(7.5) has nearly no effect on the solutions of *HET* and a relatively great impact on the feasibility of test cases

Table 16 Scenario E: relative deviations from *HET*

g	*HET-A* (%)	*HET-B* (%)	*E-HOM*(7.5) (%)	*DE-HOM*(7.5) (%)	*E-HOM*(18) (%)	*DE-HOM*(18) (%)	*C-HOM*(7.5) (%)	*C-HOM*(18) (%)
1	1.87	5.85	1.88	13.94	36.22	48.49	19.18	39.67
2	5.92	1.32	–	8.46	28.31	40.24	12.71	29.46
3	–	– 1.99	–	5.01	20.43	31.89	6.02	21.65
4	–	– 0.87	–	–	24.90	30.60	4.98	19.45

for *E-HOM*(7.5). All test cases with a maximal customer distance below 105 km become feasible for *DE-HOM*(7.5). For distances below 35 km however, the optimal values for travel time respectively energy consumption are increased by 6% respectively 12%. For distances between 35 km and 105 km *DE-HOM*(7.5) is the most energy efficient homogeneous fleet. Augmenting the battery size for vehicles of type *EV*(18) has no positive effect on the solutions of *HET* and *E-HOM*(18). Quite the contrary, the solution quality has been declined by battery augmentation.

Comparing Scenario T with Scenario E shows that minimizing energy consumption instead of travel time leads to substantially more energy efficient transportation plans only for heterogeneous fleets. Finally, the search for attractive heterogeneous fleets has demonstrated that it is possible to configure highly energy- and time-efficient heterogeneous fleets with a reasonable number of vehicles. For future research, it will be challenging to develop approaches for optimizing the size and composition of heterogeneous fleets. Furthermore, it may be attractive to apply methods of multi-criteria optimization for amalgamating the travel time minimization of Scenario T with the energy minimization of Scenario E.

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