# Vehicle Routing with a Heterogeneous Fleet of Combustion and Battery-Powered Electric Vehicles under Energy Minimization

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**Abstract.** This paper compares energy minimization with minimizing distance and travel time in vehicle routing. The focus is on the influence of the objective chosen when deploying homogeneous and heterogeneous vehicle fleets. To achieve that, vehicles with different capacities and ranges as well with combustion engines as with battery-powered electric engines are taken into consideration. Results show that when deploying homogeneous fleets there are no significant differences between the optimal solutions when using energy minimization instead of distance or time minimization. Hence, the potential for reducing energy consumption of distance or time optimal solutions is very small with homogeneous fleets. By contrast, when deploying a heterogeneous fleet, a significant reduction of energy consumption in the double-digit percentage order can be achieved. On the other hand the total travel distance as well as total travel time increases. Comprehensive computational experiments show that certain fleets can be identified that consume only small amounts of additional energy compared to an idealized fleet consisting of an arbitrarily large number of vehicles of all different types. Furthermore, numerical experiments show that minimizing both the energy consumption as well as the distance, only a small number of Pareto-optimal solutions exist. The most attractive of those can be chosen easily according to practical preferences.

**Keywords:** Vehicle routing, Heterogeneous vehicle fleet, Electric versus combustion engine, Pareto optimization, Ecological objective

## 1 Introduction

In addition to traditional objectives that are typically used in vehicle routing, in recent years more work relating to ecological objectives in vehicle routing has been published in the literature on transport logistics. Most of the ecological criteria of "green vehicle routing" [6] are based on the energy consumption required to fulfill a given set of transportation requests [3]. The immediate $CO_2$ emission and the total global warming potential (i.e. the $CO_2$ equivalents, measured in $CO_2$e) depend on the amount of energy consumed for a transportation


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process and can be determined solely based on this amount of energy. Other external effects of transportation processes are not considered in this paper (see e.g. [4]). The global warming effects of energy consumption are assessed using different methods [13]. The WTW (Well-to-Wheel) analysis method takes into consideration the total energy chain required to instantiate a locomotion, i.e. from energy generation to provision of energy at the point of consumption on to transformation into kinetic energy. By contrast, the TTW (Tank-to-Wheel) analysis method focuses only on the greenhouse gas emitted locally through transformation of stored energy (in a fuel tank or battery) into kinetic energy.

In the literature, several articles are dedicated to a comparison of energy-minimizing objectives and distance-minimizing objectives in vehicle routing (e.g. [7, 10]). [14] consider energy minimization for homogeneous fleets and conclude that different types of VRPs should be remodeled by considering fuel consumption.

[5] consider a time- and load-dependent problem of minimizing $CO_2$ emissions in the routing of vehicles in urban areas. In their paper [5] present experiments on using different objective functions like minimizing distance, minimizing time-dependent travel times, minimizing time-dependent emissions based on the gross weight of a vehicle, and minimizing time-dependent emissions based on the actual weight (i.e. empty weight plus weight of the cargo) of a vehicle. In contrast to our paper, only vehicles with combustion engines and no battery-powered electric vehicles are considered by [5]. Moreover, most of the experiments are performed on TSP instances with one single vehicle which is able to serve all customers, while only a very small part of [5] refers to results obtained for fleets with multiple vehicles. Two homogeneous fleets and only one single configuration of a mixed fleet are considered. The pickup quantities are adjusted to the specific fleet capacity so that always three vehicles are required. Consequently, the test instances used in [5] vary for different fleet compositions. That is why, in contrast to our paper, a direct comparison of the solutions generated for different fleets is not possible in [5].

Results shown in [7] and [10] demonstrate that in the case of homogeneous vehicle fleets energy minimization compared to distance minimization results in very small energy savings of only a few percentage points (1% - 2%). However, in the case of heterogeneous fleets the potential to save energy is much larger. The deployment of suitably composed heterogeneous fleets can result in energy savings in the order of double-digit percentages [12]. Due to the fact that time, distance and energy are the main contributing factors to the variable cost of transport processes, the existing literature does not treat time and distance minimization as alternatives to energy minimization but as components of more comprehensive objective functions that comprise time and distance as well as energy consumption [1, 9].

This paper addresses WTW-energy-oriented criteria and the traditional criteria of time and distance in vehicle routing relating to different types of vehicles. An interesting insight derived from the study of [11] is that using a heterogeneous fleet without speed optimization allows for a further reduction in total cost than using a homogeneous fleet with speed optimization. As opposed to the paper of [12], not only vehicles with a combustion engine but also vehicles equipped with a battery-powered electrical engine will be taken into consideration. Battery-powered electric vehicles are more energy-efficient but they have a reduced driving range and a reduced payload compared to combustion-powered vehicles with the same gross weight. Particularly the following research questions will be addressed:

1. How large is the difference between energy-optimal solutions compared to time- and distance-optimal solutions concerning the following criteria: energy consumed, total travel time and total travel distance needed to perform all transportation requests?
2. Are the impressive energy savings by deploying idealized heterogeneous fleets with a flexible number of vehicles [12] instead of homogeneous fleets only achieved by exploiting the degrees of freedom given by the choice of vehicles from an unlimited vehicle pool; in other words: can fixed fleet configurations be identified that yield high energy savings for all instances of a given planning scenario?
3. How can an efficient heterogeneous fleet with a small number of available vehicles be determined and how large is the loss of efficiency compared to an idealized fleet with an arbitrarily large number of vehicles of each type?
4. What are the properties of the Pareto set in multi objective optimization, particularly in Pareto optimization concerning the two objectives energy and distance minimization?

## 2 Planning Scenarios and Vehicle Properties

As a basis for the specification of planning scenarios used to conduct an analysis to answer the above research questions the well-known CVRP is chosen [2]. The CVRP has a distance-oriented objective that minimizes the total travel distance of all vehicles dispatched. In addition to the capacity restrictions concerning the maximum payload, the planning scenarios analyzed in this paper take into consideration the range of the vehicles. The maximal length of a tour is limited by a given parameter. The CVRP with additional range limitations shall be called distance-based vehicle routing problem TP-D. The TP-D is transformed into a time-based vehicle routing problem TP-T by using the objective of minimizing total time needed for all tours instead of total distance. The constant vehicle specific average speed $v_k$ of vehicle $k$ converts travel distance into travel time. For the energy-oriented vehicle routing problem TP-E the energy consumption for the execution of tours is estimated as a function of the mass moved and the distance the mass is moved. It is generally accepted that the following equation (1) is a suitable approximation for a simplified estimation of the energy consumption $F_k(i, j)$ of vehicle $k$, that transports goods of the mass $q_{ij}$ from location $i$ to location $j$ (see e.g. [14]).

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

The symbol $d_{ij}$ denotes the distance between location $i$ and location $j$, while $a_k$ and $b_k$ denote vehicle specific parameters for energy consumption. As a result, the objective criterion of the optimization problem TP-E consists of the total estimated energy consumption for all tours.

This paper considers four different types of vehicles: two smaller types with a gross weight of 7.5 metric tons each and two larger types with a gross weight of 18 tons each. Two vehicle types are equipped with a conventional combustion engine, one of them with 7.5 tons (sCV) and the other with 18 tons (lCV) gross weight. The other two vehicle types are equipped with a battery-powered electrical engine, one with 7.5 tons (sEV) and the other with 18 tons (lEV) gross weight. Those types of vehicles are available on the commercial vehicle market and are typically used for local pickup or delivery. The characteristic parameters for payload and energy consumption shown in Table 1 can be found in technical specifications of vehicle manufacturers or derived from descriptions provided by manufacturers. The maximal daily tour length of 600 km limits the range of all vehicles; for vehicles equipped with an electrical engine, the maximal energy available (i.e. the battery capacity) additionally limits the range. Smaller vehicles of type sEV have a battery capacity of 601 MJ and larger vehicles of type lEV have a battery capacity of 2,425 MJ. The actual range of those vehicles depends on the load while en route. Table 1 shows a lower and an upper value, where the lower value corresponds to a vehicle fully loaded and the upper value corresponds to an empty vehicle. For all vehicles with more than 3.5 tons gross weight, the legal speed limit on German highways (i.e. BAB or Kraftfahrstraßen) is 80 km/h; on all other ordinary non-urban roads the speed limit is 60 km/h for vehicles of more than 7.5 tons gross weight. Assuming that this difference in speed limits is incurred for one third of any tour, the smaller vehicles (sCV und sEV) are approximately 10% faster than the larger vehicles (lCV und lEV).

**Table 1.** Characteristics of the vehicle types considered

| Vehicle type | Payload [t] | Range [km] | $a_k$ [MJ/km] | $b_k$ [MJ/km] | $v_k$ [km/h] |
|---|---|---|---|---|---|
| sCV | 4.0 | 600 | 5.77 | 0.36 | 55 |
| sEV | 3.5 | 98 – 140 | 4.27 | 0.53 | 55 |
| lCV | 9.0 | 600 | 7.99 | 0.29 | 50 |
| lEV | 6.0 | 253 – 300 | 7.80 | 0.24 | 50 |

## 3 Model

The mathematical model for the energy-oriented vehicle routing problem TP-E is an extension of the CVRP [2]. The important extensions address on the one hand the objective function of the model in order to introduce and minimize vehicle specific values concerning the load-based energy consumption. On the other hand, the constraints have to ensure the maximal tour length, concerning the electric vehicles caused by the limited battery capacity.

Indices:

| | |
|---|---|
| $i$,$j$ | Nodes: $i$,$j \in N = \{0, 1, ..., n, n+1\}$, where 0 and $n+1$ represent the depot and $C = \{1, ..., n\}$ represents the customers |
| $k$ | Vehicle $k \in K = \{1, ..., m\}$ |

Parameters:

| | |
|---|---|
| $d_{ij}$ | Distance between nodes $i$ and $j$ |
| $tt_{ijk}$ | Travel time of vehicle $k$ on the arc from $i$ to $j$ |
| $\pi_j$ | Customer's demand in node $j = 1, ..., n$ |
| $s_j$ | Service time at customer $j = 1, ..., n$ |

Constants:

| | |
|---|---|
| $a_k$ | Energy consumption of the empty vehicle $k$ per kilometer |
| $b_k$ | Energy consumption for the load of vehicle $k$ per ton and kilometer |
| $E_k$ | Energy supply of vehicle $k$ when leaving the depot |
| $T_k$ | Maximal tour length of vehicle $k$ |
| $Q_k$ | Maximal payload capacity of vehicle $k$ |

Variables:

| | |
|---|---|
| $e_{ijk}$ | Energy content available for vehicle $k$ traversing the arc from $i$ to $j$ |
| $q_{ijk}$ | Weight of load in vehicle $k$ on the arc from $i$ to $j$ |
| $x_{ijk}$ | 1, if vehicle $k$ uses the arc from $i$ to $j$<br>0, else |
| $y_{jk}$ | 1, if customer $j$ is serviced by vehicle $k$<br>0, else |

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

subject to

$$\sum_{j=1}^{n+1} x_{0jk} = 1 \qquad \forall k \in K \tag{3}$$

$$\sum_{i=0}^{n} x_{in+1k} = 1 \qquad \forall k \in K \tag{4}$$

$$\sum_{j=0}^{n+1} x_{n+1jk} = 0 \qquad \forall k \in K \tag{5}$$

$$\sum_{i=0}^{n} x_{ijk} - \sum_{i=1}^{n+1} x_{jik} = 0 \qquad \forall j \in C, \forall k \in K \tag{6}$$

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

$$\sum_{i=0}^{n} x_{ijk} = y_{jk} \qquad \forall j \in C, \forall k \in K \tag{8}$$

$$\sum_{j=0}^{n+1} \pi_j \cdot y_{jk} \leq Q_k \qquad \forall k \in K \tag{9}$$

$$x_{iik} = 0 \qquad \forall i \in N, \forall k \in K \tag{10}$$

$$\sum_{i=0}^{n+1} q_{ijk} - \sum_{i=0}^{n+1} q_{jik} = \pi_j \cdot y_{jk} \qquad \forall j \in C, \forall k \in K \tag{11}$$

$$q_{ijk} \leq Q_k \cdot x_{ijk} \qquad \forall i, j \in N, \forall k \in K \tag{12}$$

$$\sum_{i=0}^{n+1} \sum_{j=0}^{n+1} d_{ij} \cdot x_{ijk} \leq T_k \qquad \forall k \in K \tag{13}$$

$$\sum_{i=0}^{n+1} d_{ij} \cdot (a_k \cdot x_{ijk} + b_k \cdot q_{ijk}) = \sum_{i=0}^{n+1} e_{ijk} - \sum_{i=1}^{n+1} e_{jik} \qquad \forall j \in C, \forall k \in K \tag{14}$$

$$d_{ij} \cdot (a_k \cdot x_{ijk} + b_k \cdot q_{ijk}) \leq e_{ijk} \qquad \forall i, j \in N, \forall k \in K \tag{15}$$

$$E_k \cdot x_{0jk} = e_{0jk} \qquad \forall j \in N, \forall k \in K \tag{16}$$

$$e_{ijk} \leq E_k \cdot x_{ijk} \qquad \forall i, j \in N, \forall k \in K \tag{17}$$

$$q_{ijk} \geq 0 \qquad \forall i, j \in N, \forall k \in K \tag{18}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall i, j \in N, \forall k \in K \tag{19}$$

$$y_{ik} \in \{0, 1\} \qquad \forall i \in N, \forall k \in K \tag{20}$$

The objective function (2) minimizes the total energy required for all tours. The equations / inequalities (3) through (10) represent the usual constraints for modeling the CVRP. Equations (11) guarantee that the required demand $\pi_j$ is unloaded at customer $j$ and the load of the vehicle $k$ is reduced accordingly. Inequalities (12) ensure that the loads $q_{ijk}$ are zero if vehicle $k$ does not use arc $(i,j)$. Inequalities (13) limit the maximal tour length for each vehicle $k$. Equalities (14) determine the remaining energy supply at customer $j$ in vehicle $k$. Equalities / inequalities (15), (16), and (17) ensure that the remaining energy supply in vehicle $k$ to cover the arc from $i$ to $j$ is between the maximal possible and the minimal required energy supply. Relations (18), (19), and (20) define the domains of variables $q_{ijk}$, $x_{ijk}$ and $y_{jk}$.

$$\min \sum_{i=0}^{n+1} \sum_{j=0}^{n+1} \sum_{k=1}^{m} d_{ij} \cdot x_{ijk} \tag{21}$$

$$\min \sum_{i=0}^{n+1} \sum_{j=0}^{n+1} \sum_{k=1}^{m} (tt_{ijk} + s_j) \cdot x_{ijk} \tag{22}$$

The MIP formulation of TP-E above aims at minimizing the total energy consumption. In order to minimize total travel distance in the model of the distance-based vehicle routing problem TP-D objective function (21) replaces objective function (2). To minimize total travel time in the time-based vehicle routing problem TP-T the objective function (22) replaces (2).

## 4 Generating Test Instances

The analysis regarding the research questions listed above is conducted using specific problem instances with short travel distances corresponding to inner city transportation or pickup / delivery tours in rural areas. To solve the problem instances of the vehicle routing problems TP-D, TP-T and TP-E, the commercial solver IBM ILOG CPLEX 12.6.1 is used. To obtain reliable results for the further analysis, only small instances are generated that can be expected to be solved to optimality using CPLEX on a PC. Initially, generic problem instances with eight customers are generated. Customers' demands are measured in tons and evenly distributed over the interval $[1, 3]$; i.e., the values for customers 1 through 8 are: 1.0 / 1.3 / 1.6 / 1.9 / 2.1 / 2.4 / 2.7 / 3.0. Altogether, 50 different generic problem instances with the above-mentioned eight customers are generated. The coordinates of the eight customer locations are determined randomly for each generic instance. Coordinates are within a geographic area of 30 km $\times$ 30 km; i.e. they are randomly located within a grid square of $[0, 30] \times [0, 30]$. The depot of the vehicle routing problem is located in the middle of the grid square, i.e. at coordinates $(15, 15)$.

Based on the previously generated 50 generic random problem instances, concrete test instances are generated by the following two additional problem specifications:

(a) First of all, the available vehicle fleet is specified. Five different fleet configurations will be considered: one homogeneous fleet sC-HOM with eight vehicles of type sCV, one homogeneous fleet sE-HOM with eight vehicles of type sEV, one homogeneous fleet lC-HOM with eight vehicles of type lCV, one homogeneous fleet lE-HOM with eight vehicles of type lEV and one heterogeneous fleet HET, that consists of all of the above-mentioned homogeneous fleet configurations, i.e. eight vehicles of type sCV, sEV, lCV, lEV each.

(b) Secondly, a gauge factor $g$ is introduced that varies the distances between all relevant locations of the test instances. The factor $g$ has the values 1, 2, 3, and 4, which are used to scale the original grid square. By scaling, the grid square is enlarged and all distances between relevant locations (depot, customers) are multiplied with the gauge factor. The depot remains in the original location in the middle of the grid square in all instances.

The size of the vehicle fleets in (a) was chosen such that the total available payload is definitely sufficient to service all customers. The accumulated weight of all eight customer demands is 16 tons; when deploying eight vehicles of a homogeneous fleet, a maximal demand between 28 and 72 tons can be transported, depending on the vehicle type. More than eight vehicles will never be dispatched because all test instances feature exactly eight customers. The heterogeneous fleet HET is an idealized fleet composed in such a way that the solution space when using HET is larger than with any of the homogeneous fleets. The values of the gauge factor $g$ in (b) are chosen in such a way that the range of the vehicles in fleet sE-HOM is sufficient to reach all customers in the grid square in a pendulum tour for $g \leq 2$. If $g > 2$ it is to be expected that some test instances are infeasible due to the limited range of the vehicles in fleet sE-HOM. The range of the vehicles in fleet lE-HOM is sufficiently large to ensure feasibility of all test instances with $1 \leq g \leq 4$. For instances with $g > 4$ that are not considered in this paper, the range of vehicles of type lEV may not be sufficient in all instances. In this case, the deployment of vehicles with combustion engine cannot be avoided.

Service times for all scenarios and instances are chosen to be $s_0 = 0$ (depot) and $s_j = 15$ min (each customer).

## 5 Analysis of Optimal Transportation Plans

In this section, research questions (1) through (3) are investigated. All 3,000 test instances (50 generic problem instances, 3 planning scenarios, i.e. objectives, 4 values of the gauge factor, 5 different vehicle fleets) can be solved to optimality using CPLEX. As was to be expected, deploying fleet sE-HOM optimal solutions for all test instances with $g \leq 2$ can be found. For $g = 3$ feasible solutions exist for 47 out of 50 instances. Due to the limited range of vehicles of type sEV, experiments show that only 10 out of 50 test instances with $g = 4$ are feasible. Let oTP-E, oTP-D and oTP-T denote an attribute (#Tours, Time, Distance, Energy) of the optimal solution of TP-E, TP-D and TP-T, respectively. Table 2 lists the relative differences ((oTP-E − oTP-T) / oTP-E, and (oTP-E − oTP-D) / oTP-E), respectively, that can be achieved by energy minimization instead of time respectively distance minimization concerning the number of vehicles

**Table 2.** Energy minimization versus time and distance minimization

| Fleet | Time minimization | | | Distance minimization | | |
|---|---|---|---|---|---|---|
| | $\Delta$#Tours | $\Delta$Time | $\Delta$Energy | $\Delta$#Tours | $\Delta$Distance | $\Delta$Energy |
| sC-HOM | 2.0% | 0.0% | -0.1% | 2.0% | 0.03% | -0.1% |
| sE-HOM | 2.7% | 0.1% | -0.3% | 2.3% | 0.1% | -0.2% |
| lC-HOM | 8.9% | 0.3% | -0.4% | 8.9% | 0.4% | -0.4% |
| lE-HOM | 5.9% | 0.1% | -0.2% | 5.9% | 0.1% | -0.2% |
| HET | 51.5% | 21.3% | -13.3% | 54.2% | 21.4% | -14.7% |

deployed, total travel time, total distance traveled, and energy consumed. As a matter of course, the values in Table 2 for the fleet sE-HOM only include test instances, that are guaranteed to be feasible, i.e. test instances with $g = 1$ or $g = 2$.

The results in Table 2 provide an answer to research question (1). They show that significant differences between optimal solutions that are found minimizing on the one hand distance or time and on the other hand energy can only be observed with a heterogeneous vehicle fleet. The differences between time and distance minimization caused by the differing average speed of the vehicles are very small. In detail, the differences when using the fleet HET are the following: Independent of the value of the gauge factor $g$ distance-minimizing solutions to TP-D need on average 0.1% more travel time than corresponding time-minimized solutions to TP-T. Reciprocally, optimal solutions to TP-T independent of the value of $g$ result on average in 0.16% longer tours compared to TP-D. Furthermore, results show that distance-minimized solutions compared to time-minimized solutions consume on average 1.2% more energy but require a 5.9% smaller number of vehicles, independent of the value of $g$. For homogeneous fleets no differences between time-oriented and distance-based optimization can be observed concerning distance traveled, time needed and energy consumed. Larger differences concerning required energy, time and distance are only to be expected in extended scenarios where electric vehicles can recharge batteries en route at external charging stations.

A detailed analysis of the optimal solutions to the test instances generated for HET will contribute to answering research question (2). The analysis will focus on the use of different vehicle types in the solutions. This will provide insight into the question whether certain vehicle configurations are optimal for a larger number of test instances. Among the 200 test instances solved under energy optimization, 34 instances have an optimal solution that deploys a homogeneous vehicle fleet. Furthermore, a great variety of different fleets yields optimal solutions. For each value of $g$ each vehicle type is deployed in at least one of the 50 test instances, i.e. none of the vehicle types is dispensable when generating optimal solutions. A cursory analysis does not provide any indication that for a certain value of $g$ a specific fleet configuration or specific properties of fleets deployed are advantageous to yield optimal solutions. However, an in-depth analysis shows that in some cases certain fleet configurations are optimal for all values of $g$ for some of the generic test instances. This indicates that the properties of an optimal heterogeneous fleet are mainly dependent on the customers' locations and on their demands, but little on the distances between the customers, as long as the distances vary only within a given spectrum of factor 4.

The idealized fleet HET comprises eight vehicles per vehicle type, thus 32 vehicles. Optimal solutions to the planning scenario TP-E require maximal 3, 6, 2, 1 vehicles of the types sCV, sEV, lCV and lEV, respectively. Consequently, a fleet configured accordingly with 12 vehicles would be sufficient to find the same optimal solutions as to the idealized fleet.

To address research question (3): Optimal solutions to the planning scenario TP-E using the idealized fleet HET require in the test sets on average (0.6/3.1/0.6/0.1) vehicles of types (sCV/sEV/lCV/lEV). Rounding the average number of vehicles to the next integer and using at least one vehicle of each type, the result is a heterogeneous fleet of six vehicles (HET6), comprising (1/3/1/1) of the vehicle types specified above. Promising fleets of five vehicles can be developed by either surrendering the vehicle lEV or the vehicle sCV contained in HET6. Hence, the fleets HET5-A = (1/3/1/0) and HET5-B = (0/3/1/1) with five vehicles each are derived. The relative differences ((oTP-E − oTP-T) / oTP-E, and (oTP-E − oTP-D) / oTP-E), respectively, that are achieved by energy minimization instead of distance minimization concerning the energy consumption are -9.0% (for HET6), -5.7% (for HET5-A), and -8.5% (for HET5-B). For a comparison of these values with the relative differences that have been computed for the other fleets, Table 2 can be consulted. Table 3 compares the energy consumption of different fleets. The reference value is the energy consumed by HET; i.e. the table lists the relative differences in energy consumption (on average over all values of $g$) of the homogeneous and heterogeneous fleets considered in relation to the energy consumption of the idealized fleet HET (i.e. the additional energy consumption of these fleets compared to HET). For sE-HOM the comparison is only performed for $g \leq 2$, because for test instances with $g = 3$ and $g = 4$ not all of the instances are feasible. Therefore, the value for sE-HOM in Table 3 is displayed in parenthesis. A comparison of sE-HOM with HET6, HET5-A, and HET5-B, respectively, shows that sE-HOM (on average over all values of $g \leq 2$) consumes on average 3.36%, 3.14%, and 2.38%, respectively, more energy than the respective heterogeneous fleets.

**Table 3.** Increase of energy consumption compared to HET

| sC-HOM | sE-HOM | lC-HOM | lE-HOM | HET6 | HET5-A | HET5-B |
|---|---|---|---|---|---|---|
| 17.98% | (4.92%) | 13.73% | 23.14% | 1.13% | 1.60% | 3.22% |

## 6 Energy-Efficient Fleets and Multi Criteria Analysis

This section is dedicated to an intensified investigation of research question (3); and research question (4) will be investigated in-depth. Based on the outcomes of Section 5 concerning research question (3), it suggests itself to investigate test instances using fleets consisting of exactly five vehicles when trying to identify efficient fleets and Pareto-optimal solutions. F(5) denotes the set of all five-element vehicle fleets that consist of the four vehicle types defined in Section 2. To determine energy-efficient fleets and to perform multi criteria analysis concerning energy and distance-efficient solutions, the test instances of Section 4 will be used. The test instances of Section 4 represent a transportation scenario for less-than-truckload shipments with weights between one and three tons in a distribution area characterized by distances of up to 21 km for $g = 1$ (length of half the diagonal of the grid square). For greater values of the gauge factor $g$, the maximum distances within the distribution area are increased correspondingly. To determine the most efficient fleets consisting of five vehicles (research question (3)) and to determine the properties of Pareto sets under multi criteria vehicle routing for heterogeneous fleets, a brute-force approach is chosen. Systematically, all eligible fleets consisting of five vehicles are tested and the corresponding vehicle routing problems are solved.

When generating a fleet out of the set F(5), five elements have to be chosen out of a basic set of four vehicle types. The elements (vehicle types) may be chosen multiple times and the sequence is irrelevant. Hence, there are $((5 + 4 - 1)/5) = 56$ different possibilities to configure a fleet out of the set F(5). Using the brute-force approach to determine the energy efficiency of all possible five-element fleets out of F(5) for all 200 test instances (50 generic problem instances, 4 values for the gauge factor), the energy-optimized solutions to the vehicle routing problem TP-E have been computed for each of the 56 different fleets. Consequently, applying the brute-force approach 11,200 (56 x 200) vehicle routing problems were solved. Numerical experiments show that the fleet (1/3/1/0) actually is the most energy-efficient fleet out of all 56 fleets in F(5). The fleet (1/3/1/0) was already considered in Section 5 and denoted by HET5-A (see also Table 3). Concerning the energy efficiency on average over all gauge factors $g$, HET5-A is the only fleet that is only less than 2% worse than the idealized fleet HET. Only three other fleets ((1/2/0/2), (1/2/1/1), and (2/2/1/0), respectively) show differences of less than 3% compared to HET with 2.19%, 2.19%, and 2.35%, respectively. The above-mentioned fleet (1/2/0/2) consists of four electric vehicles and one conventional vehicle with a diesel engine. In the fleet configurations (1/3/1/0) and (1/2/1/1) three electric vehicles and two conventional vehicles with a combustion engine are deployed, and the fleet (2/2/1/0) uses two electric vehicles and three conventional vehicles. Half of all the fleets in F(5) result in a relatively poor energy consumption with a difference above 8% compared to HET. The average difference over all fleets in F(5) where all instances with all gauge factors could be solved is 8.96%. Poorest performance of all heterogeneous fleets could be observed at fleet (1/0/0/4) with a difference of 18.44%. Homogeneous fleets result in particularly large differences. They are 23.15% for (0/0/0/5), 13.73% for (0/0/5/0), and 18.1% for (5/0/0/0). Comparing homogeneous fleets, the performance of conventional vehicles is superior to electric vehicles. Hence, the homogeneous fleet of vehicles of type lCV consumes considerably less energy than the homogeneous fleet with small conventional vehicles, which again consumes considerably less energy than the homogeneous fleet consisting of large electric vehicles. For the homogeneous fleet (0/5/0/0) with small electric vehicles a comparison of energy consumption with HET is not possible, because feasible solutions do not exist for all test instances using such a homogeneous fleet. The variation of the gauge factor $g$ has only a small influence on the energy efficiency of the best fleets. HET5-A is the best fleet for the values $g = 1$, $g = 2$, and $g = 3$. For $g = 4$ the fleet (1/2/2/0) yields slightly better results. Note that this fleet is very similar to HET5-A, because it evolves by exchanging one vehicle of type sEV by type lCV.

A detailed analysis of the optimal solutions obtained with HET5-A shows that only 16.5% of all 200 test instances have solutions actually using all five vehicles in HET5-A. All the other test instances yield better solutions deploying only four and in one case even only three vehicles than any five-element fleet configuration. For 46% of all test instances, the fleet (0/3/1/0) can be identified as the best possible fleet to obtain optimal vehicle routes, i.e. the vehicle of type sCV is not used. For 29.5% of all instances the third vehicle of type sEV is not used (fleet (1/2/1/0)), and for another 8% of all instances only one of the three vehicles of type sEV is actually deployed (fleet (1/1/1/0)). It is remarkable that the fleet yielding the best results for nearly half of all test instances (i.e. (0/3/1/0)) deploys as well electric as combustion engine vehicles, namely three small electric vehicles and one large combustion engine vehicle.

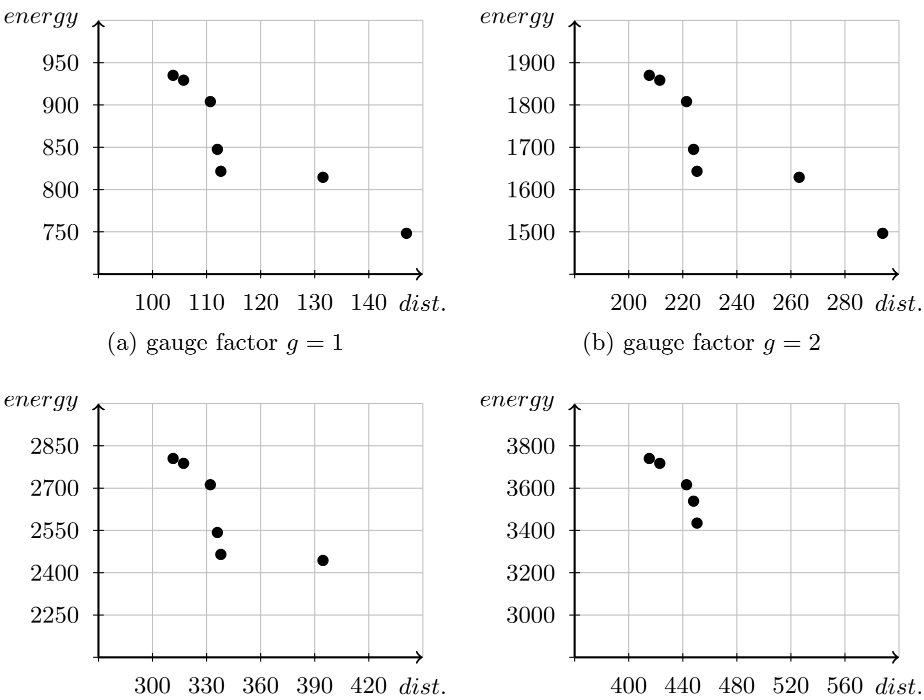
The analysis of the solutions obtained with the idealized fleet HET shows that for after all 38 out of 200 test instances the best results could be found with fleets consisting of six vehicles. Insofar it is remarkable that HET5-A with only five vehicles yields results that are only 1.6% inferior to HET. The reason may be that for 56 out of 200 test instances the fleet (0/3/1/0) and for 28 out of 200 instances the fleet (1/2/1/0) is the most energy-efficient one. Both fleets are included in HET5-A.

By means of the brute-force approach, it could be achieved to identify particularly energy-efficient heterogeneous fleets for the planning scenario introduced in Section 2, extended to an application scenario in Section 4 (research question (3)). It could be shown that heterogeneous fleets with a small number of vehicles exist that are nearly as energy-efficient as the idealized fleet HET. Hence, the large potential for energy savings through heterogeneous instead of homogeneous fleets is not caused by the large variety and flexibility of an idealized fleet (research question (2)), but can also be put into effect using a specific small vehicle fleet with an appropriate number of vehicles. To investigate research question (4), all elements of the Pareto set in a bicriteria optimization for three selected fleets shall be determined, again using a brute-force approach. Whether this is possible at all depends on the cardinality of the Pareto sets.

Due to the fact shown in Section 5 that the differences between objective function values comparing optimal solutions to distance minimization with time minimization are very small, it can be assumed that a Pareto optimization comparing energy- and time-optimal solutions on the one hand and comparing energy- and distance-optimal solutions on the other hand will result in similar values. Hence, the analysis conducted in this section in the framework of a multi criteria optimization will be limited to the comparison of energy minimization and distance minimization; i.e. the comparison of the optimization criteria energy minimization and time minimization will not be undertaken. In order to determine the Pareto sets to be investigated, for the idealized fleet HET, for the best known heterogeneous fleet with five vehicles HET-5A, and for the most energy-efficient homogeneous fleet (0/0/5/0) all 200 test instances (with 50 generic problem instances and 4 different gauge factors) are considered. Altogether 600 Pareto sets will be determined.

To determine the Pareto set of a test instance, at first the energy-optimal solution P1 is computed by solving the vehicle routing problem TP-E for this test instance. Thus, the first element of the Pareto set is found. Subsequently, an additional constraint R1 is inserted into TP-E that ensures that the sum of all distances traveled has to be by 0.01 km smaller than in solution P1, and, if it exists, a second element P2 of the Pareto set can be found by solving the problem that has been extended with R1. All other Pareto-optimal solutions are determined iteratively by requiring that any additional solution has a total travel distance that is at least 0.01 km shorter than the immediately preceding solution. This is repeated until the optimization problem to be solved does not have a feasible solution due to the latest of the inserted constraints.

Among the 200 Pareto sets that have been determined for the idealized fleet HET, there are two sets consisting of 17 Pareto-optimal solutions. All other Pareto sets have a smaller number of Pareto-optimal solutions, and some Pareto sets consist of only one element. On average, the 200 Pareto sets of the fleet



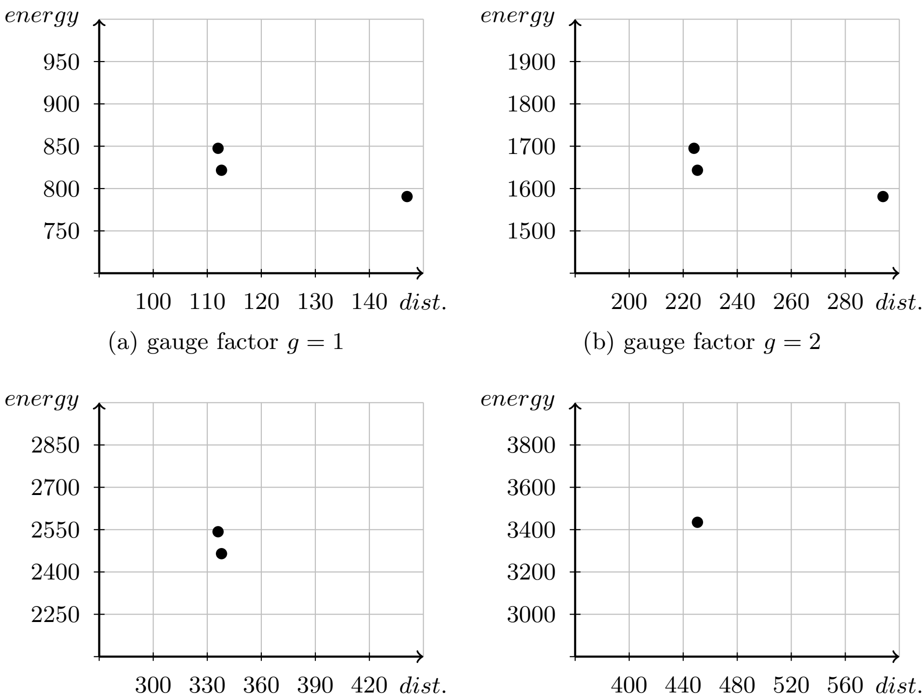

(a) gauge factor $g = 1$ (b) gauge factor $g = 2$

(c) gauge factor $g = 3$ (d) gauge factor $g = 4$

**Fig. 1.** Pareto frontiers of fleet HET

HET possess a cardinality of 6, 6, 6, and 5, for $g = 1$, $g = 2$, $g = 3$, and $g = 4$, respectively. Thus to determine the Pareto sets of HET, approximately 1,200 vehicle routing problems were solved. The Pareto sets computed for the fleet HET-5A possess a maximal cardinality of 8 and a minimal cardinality of 1. The average values of cardinality are 3, 3, 3, and 2, for $g = 1$, 2, 3, and 4, respectively. For the most energy-efficient homogeneous fleet (0/0/5/0) the maximal, average, and minimal cardinality is 3, 1, and 1, respectively.

Overall, it can be observed that the Pareto sets are relatively small. Due to the small cardinality of the Pareto sets, it is entirely reasonable and easily possible to utilize the Pareto sets for a subsequent selection process where the most attractive Pareto-optimal solution is chosen to match specific decision criteria according to a given purpose. Figures 1 and 2 display the Pareto frontiers of fleets HET and HET5-A at different values of the gauge factor $g$ for one selected generic problem instance. In order to obtain as large a distance as possible between the extreme values in the Pareto sets, the particular instance out of all 50 generic problem instances that shows the largest differences of all instances between solutions to TP-E and TP-D for HET-5A is selected for display in Figures 1 and 2.




(a) gauge factor $g = 1$

(b) gauge factor $g = 2$

(c) gauge factor $g = 3$

(d) gauge factor $g = 4$

**Fig. 2.** Pareto frontiers of fleet HET5-A

## 7 Results and Future Research

The numerical experiments were deliberately performed using small instances in order to be able to obtain optimal solutions as a basis for the analysis. Because generating suboptimal solutions, as they will typically be found when applying heuristics to larger instances, and then using those to perform comparisons and draw conclusions carries the considerable risk of false conclusions (see already [8]). This particularly holds when no knowledge is available about the average- or worst-case behavior of the heuristics applied, which is frequently the case. Hence, the results used for answering the questions (1) to (4) are based solely on the above mentioned small test instances. Since the tests do not exploit any specific attributes of small CVRP test instances, we believe that experiments on large instances would yield similar answers to our questions. In order to prove whether the found answers are not restricted to small CVRP instances, algorithms capable of handling larger instances will be developed in future work.

The experiments show that there are significant differences concerning energy consumption of heterogeneous vehicle fleets between energy-optimal solutions on the one hand and distance-optimal or time-optimal solutions on the other hand (see Table 1). In an idealized heterogeneous fleet with a sufficiently large number of vehicles, all types are used; and the degrees of freedom that exist due to the plenitude of available vehicles when configuring a fleet is actually exploited in order to generate flexibly energy-efficient fleets adapted to the specific transportation requests. Nevertheless, in the numerical experiments heterogeneous fleets with a small number of fixed vehicles could be identified that show an energy efficiency that is only a few percentage points worse than that of the idealized fleet (see Table 3). Furthermore, a systematical search evaluating all conceivable fleets with only five vehicles succeeds in identifying within the analyzed application scenario the most energy-efficient fleet among all five-element fleets and succeeds to show that this fleet is nearly as efficient as the idealized heterogeneous fleet. Additionally, it is shown that the Pareto sets in multi criteria optimization with energy and distance minimization are manageably small and well suitable as a starting point for a subsequent selection of customized solutions.

When utilizing heterogeneous fleets, the resulting optimal solution frequently consists of a large number of tours, particularly when many small vehicles are used that execute especially short tours. A large number of tours does not necessarily imply that the same number of vehicles/drivers are required, because multiple use of vehicles is not considered in this paper. Consequently, the models introduced in this paper shall be amended in order to be able to take into consideration multiple use of the vehicles.

To entirely exploit the potential of electric vehicles, scenarios will be evaluated where recharging of batteries en route at external charging stations or exchange of batteries at the vehicle depot is possible. This will obviously have a considerable impact on the time electric vehicles need to execute a tour and furthermore, this may require detours to charging stations. With respect to a cost analysis it should be noted that energy consumption, time needed to execute tours and total distance traveled are the dominating factors when minimizing the variable cost in vehicle routing.

## References


1. Bektaş, T. and Laporte, G.: The pollution-routing problem, Transportation Research Part B: Methodological, 45(8), pp. 1232 – 1250 (2011)
2. Dantzig, G.B. and Ramser, J.H.: The truck dispatching problem, Management Science, 6(1), pp. 80 – 91 (1959)
3. Demir, E. and Bektaş, T. and Laporte, G.: A review of recent research on green road freight transportation, European Journal of Operational Research, 237(3), pp. 775 – 793 (2014)
4. Dethloff, J. and Seelbach, H.: Umweltorientierte Logistik, In: Hansmann, K.-W. (eds.) Umweltorientierte Betriebswirtschaftslehre, pp. 145-190. Gabler, Wiesbaden (1998)
5. Ehmke, J. F. and Campbell, A. M. and Thomas, B. W.: Vehicle routing to minimize time-dependent emissions in urban areas, European Journal of Operational Research, 251(2), pp. 478 – 494 (2016)
6. Eglese, R. and Bektaş, T.: Green vehicle routing, In: Toth, P. and Vigo, D. (eds.) Vehicle routing: problems, methods and applications (2nd edition), pp. 437 – 458 Philadelphia: MOS-SIAM Series on Optimization 18 (2014)
7. Figliozzi, M.: Vehicle routing problem for emissions minimization, Transportation Research Record: Journal of the Transportation Research Board, 2197(1), pp. 1 – 7 (2010)
8. Geoffrion, A. M. and Van Roy, T. J.: Caution: Common sense planning methods can be hazardous to your corporate health, Sloan Management Review, 20(4), pp. 31 – 42 (1979)
9. Goeke D. and Schneider, M.: Routing a mixed fleet of electric and conventional vehicles, European Journal of Operational Research, 245(1), 81 – 99 (2015)
10. Kara, I. and Kara, B.Y. and Yetis, M.K.: Energy minimizing vehicle routing problem, In: Dress, A. and Xu, Y. and Zhu, B. (eds.) Combinatorial optimization and applications, pp. 62 – 71, Springer, Berlin / Heidelberg (2007)
11. Koç, Ç. and Bektaş, T. and Jabali, O. and Laporte, G.: The fleet size and mix pollution-routing problem, Transportation Research Part B: Methodological, 70, pp. 239 – 254 (2014)
12. Kopfer, H.W. and Schönberger, J. and Kopfer, H.: Reducing greenhouse gas emissions of a heterogeneous vehicle fleet, Flexible Services and Manufacturing Journal, 26(1), pp. 221 – 248 (2014)
13. Schmied, M. and Knörr, W.: Calculating GHG emissions for freight forwarding and logistics services in accordance with EN 16258, European Association for Forwarding, Transport, Logistics and Customs Services (CLECAT) (2012)
14. Xiao, Y. and Zhao, Q. and Kaku, I. and Xu, Y.: Development of a fuel consumption optimization model for the capacitated vehicle routing problem, Computers & Operations Research, 39(7), pp. 1419 – 1431 (2012)