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A Review of Heterogeneous Vehicle Routing Problems involving Electric Vehicles

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Abstract. This work is a review of papers published in the literature about vehicle routing problems with heterogeneous fleets, involving only electric vehicles or both electric and conventional vehicles, for delivery applications. Environmental concerns, particularly with regard to greenhouse gas emissions, provide a strong incentive for the adoption of electric vehicles in distribution activities. Thus, it is not a surprise if distribution problems involving electric vehicles have attracted the attention of researchers in the last few years. This review is aimed at providing a state-of-the-art account of the contribution of operations research in this area.

Keywords: Vehicle routing problem, heterogeneous fleet, electric vehicles.

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1 Introduction

In most distribution problems encountered in practice, customers are served by a fleet of heterogeneous vehicles. In this case, a crucial decision is to determine the number and types of vehicles to be used, which is known as fleet dimensioning or composition. The extension of the classical capacitated vehicle routing problem (VRP) [10] to include fleet composition along with routing decisions is called the heterogeneous VRP (HVRP). Typically, vehicles differ with regard to their transport capacity, fixed cost and variable routing cost. The two main variants of the HVRP are the fleet size and mix vehicle routing problem (FSM), introduced in [23], where the number of vehicles of each type is unlimited and the heterogeneous fixed fleet vehicle routing problem (HF), introduced in [61], where the number of vehicles of each type is fixed. We refer to [32] for an extensive review of these problems, which have been studied for a long time.

The recent and rapid introduction of alternative fuel vehicles (AFVs), in particular electric vehicles (EVs), in existing fleets made of internal combustion engine vehicles (ICEVs) fueled by gas or diesel adds an even greater level of complexity to the HVRP. EVs can be either pure battery EVs (BEVs) or hybrid EVs (HEVs). As opposed to ICEVs, BEVs do not locally produce greenhouse gas (GHG) (mostly carbon dioxide, but also small amounts of methane and nitrous oxyde) or other harmful emissions like carbon monoxide, nitrogen oxides, sulfur oxides, ammonia, volatile organic compound and particular matter. Their main downside is that they need to visit recharging stations along their route due to limited battery capacity, which is time consuming and make them dependent of the available, often scarce, recharging infrastructure. In comparison, the time needed to refuel a conventional vehicle is negligible, while fuel stations are widely available. In HEVs, there is both an electric engine and an internal combustion engine, and it is possible to switch from one engine to another along the route. Also, the battery can be recharged while the internal combustion engine is used. Due to these characteristics, HEVs do not suffer from the operational range limitations of BEVs. But their heavier weight, due to the presence of two engines, make them more costly to operate. Also, GHG and other emissions are produced when the internal combustion engine is used. An important subclass of HEVs is known as plug-in HEVs (PHEVs). In these vehicles, the battery can be recharged either internally through the use of the combustion engine or externally by plugging the vehicle to an external power source.

Generally speaking, vehicle routing problems involving EVs are in the class of green vehicle routing problems (G-VRPs), a designation coined in [18]. In these problems, the fuel consumption and harmful emissions of conventional vehicles are explicitly reduced either by including their costs into the objective function [19] or by replacing them with AFVs like EVs. Thus, both economic and environmental issues are considered in G-VRPs when designing routes for a fleet of vehicles made of ICEVs, AFVs or both. A good example of a G-VRP involving only homogeneous ICEVs is the pollution routing problem (PRP) introduced in [4]. In this work, the authors exploit a fuel consumption model that accounts for different parameters like vehicle speed, curb weight (i.e, weight when the vehicle is empty), load, slope of the road, rolling resistance and others [2, 3]. In a vehicle route, all those parameters remain constant, except load and speed, which are decision variables whose values can change from one arc to another in the road network. That is, the vehicle speed and the order in which the customers are visited and the cargo is unloaded are accounted for in the objective function, which is aimed at minimizing fuel costs, pollution emission costs and driver costs. A good example of a G-VRP involving only homogeneous EVs is the electric vehicle routing problem with time windows and recharging stations (E-VRPTW), which is described in detail in the next section. As opposed to G-VRPs, traditional VRPs can only indirectly impact fuel consumption and emissions through their minimization of the traveled distance, as noted in [57]. In particular, time-dependent VRPs, where the travel times on the arcs of a road network are not necessarily constant but depend on the time of the day are noteworthy since they favor less congested routes.

Although there are reviews about G-VRPs [1, 13, 15, 39, 51] and E-VRPs [17, 30], their general scope prevents a detailed presentation of problems involving a heterogeneous fleet made only of EVs or made of both EVs and ICEVs. This review is aimed at filling this gap. In the following, Section 2 first introduces the canonical E-VRPTW. Then, Sections 3 and 4 review the literature about HVRPs involving only EVs and HVRPs involving both ICEVs and EVs, respectively. Finally, Section 5 provides concluding remarks.

2 E-VRPTW

Given that BEVs have a limited range and can recharge their battery at recharging stations, the structure of E-VRPs shares similarities with VRPs with distance constraints [36] and VRPs with intermediate replenishment facilities [9, 62].

The E-VRPTW, as introduced in [58], is derived from the VRP with time windows (VRPTW). The E-VRPTW is defined on a complete directed graph $G = (V',\, A)$, where V' is the set of vertices and A the set of arcs. We have $V' = V \bigcup F'$, where $V = \{1, ..., N\}$ is the set of customers and F' is a set of dummy vertices that are generared to allow several visits to each vertex in the set F of recharging stations. Vertices 0 and $N + 1$ are two copies of the depot, with every route starting at 0 and ending at $N + 1$. With each arc $(i,\, j) \in A$ is associated a distance d_{ij} and a travel time t_{ij}. Each customer $i \in V$ has a transport demand q_i. a service (dwell) time s_i and a time window for service $[e_i,\, l_i]$. A vehicle cannot arrive after the upper bound l_i but can arrive before the lower bound e_i, in which case it waits up to the lower bound to start the service. The homogeneous fleet of BEVs is located at the depot, each with transport capacity Q and battery capacity C. At a recharging station, the battery is recharged to full capacity C based on a recharging rate g (energy per time unit). Thus, a linear recharge function is considered and the recharging time depends on the current battery charge when the vehicle arrives at the station and battery capacity C. Similarly, an energy consumption rate h (energy consumed per distance unit) is defined. The objective is first to minimize the number of vehicles (given the high acquisition costs of EVs) and, second, the total traveled distance. An important variant reported in the literature is the E-VRPTW with partial recharge where there is no need to recharge the battery to full capacity when the vehicle visits a station [31] (see the study in [14] on the impact of allowing partial recharge versus full recharge only, as well as imposing at most one visit to a recharging station in a route versus allowing multiple visits, using an exact problem-solving methodology).

The authors have also created two sets of instances for this problem: a set of 56 large instances, each with 100 customers and 21 recharging stations, and a set of 36 small instances with 5, 10 and 15 customers with 2 to 8 recharging stations. All those instances are derived from Solomon's euclidean VRPTW test set [60]. They are divided into three classes depending of the geographical distribution of customers, that is, random (R), clustered (C) or a mix of random and clustered (RC) customers. Six subsets of instances are then created from these three classes. Subsets R1, C1 and RC1 have a short scheduling horizon, which means that each route contains only a few customers and more routes are needed to serve all customers, while subsets R2, C2 and RC2 have a long scheduling horizon and allow more customers per route. To produce the large instances with 100 customers and 21 recharging stations, one recharging station is located at the depot and the 20 remaining stations are randomly located, while considering that every customer must be reachable from the depot using at most two different recharging stations. The battery capacity is set to the maximum between (1) the charge needed to travel 60% of the average route length in the best known solution of the corresponding VRPTW instance and (2) twice the amount of the battery charge needed to travel the longest arc between a customer and a recharging station. The energy consumption rate h is set to 1, while the recharging rate g is set so that a complete recharge requires three times the average customer service time of the corresponding instance. Due to detours needed to visit recharging stations and recharging times, the original time windows in Solomon's instances often lead to infeasibility because some customers cannot be reached within their time window. Accordingly, new time windows were generated, but still based on Solomon's procedure reported in [60]. To create the small E-VRPTW instances, 5, 10 and 15 customers were first randomly selected from the 56 large instances with 100 customers, for a total of $56 \times 3 = 168$ instances. Then, after solving these instances with a variable neighborhood search (VNS) [26] combined with tabu search (TS) [20, 21], the authors only select the two instances in each subset R1, C1, RC1, R2, C2, RC2 of each size for which the largest number of recharging stations are used in the corresponding solutions, thus leading to $2 \times 6 \times 3 = 36$ instances.

3 HVRP with only EVs

In the early work reported in [63], the authors examine a HVRP with time windows using different numbers of two types of electric trucks for urban delivery. The limited range of the trucks due to battery capacity is taken into account through a constraint on the route of each vehicle. One of the two types of trucks can exchange its battery for a new one at the depot, which allows the truck to perform two routes and double its range. The objective includes fixed costs, routing costs and driver costs. A sequential insertion heuristic is applied to construct an initial solution. The latter is then improved with a local search heuristic based on typical neighborhood operators for the VRPTW [5, 6]. The test case of a company operating with only conventional ICEVs in Amsterdam shows that the solution implemented in practice is always cheaper than the solutions obtained with different numbers and types of electric trucks. However, there are solutions that improve the Net Present Value (NPV) over an horizon of four years. Furthermore, the authors observe a reduction of 19% in total distance and 90% in CO_2 emissions.

In [40], the authors propose a HVRP model with no time windows, but where pickups or deliveries at customer locations can take place. The objective to be minimized includes travel time cost and energy cost. The latter depends on recharging time (since it leads to additional driver cost) and electricity consumption, which is calculated using a formulation that accounts for the speed and load of a vehicle, similarly to the PRP in [4]. There can be multiple visits to recharging stations in a vehicle route and a full recharge is assumed for each visit. Finally, there is no a priori assumption about vehicle size and battery capacity, which means that the proposed model can handle a fleet mix. In a small case study involving 13 customers, the authors observe that an optimal solution with diesel trucks is less costly than one with EVs, due to the recharging time of EVs. However, less energy is consumed by EVs.

An extension of the E-VRPTW and the fleet size and mix vehicle routing problem with fixed costs and time windows (FSMFTW) [42], called the electric fleet size and mix vehicle routing problem with time windows and recharging stations (E-FSMFTW) is introduced in [29]. This is basically the E-VRPTW, but with (infinite) availability of different types of BEVs that differ in their transport capacity, battery capacity and acquisition cost. The objective to be minimized is a sum of the fixed costs of all vehicles used in the solution and total traveled distance. The authors first propose a set partitioning formulation of the E-FSMFTW, which is then solved with a branch-and-price (BP) algorithm. The latter is similar to BPs for the VRPTW but the pricing problem is different because constraints related to charging must be considered. The pricing problem, a shortest path problem with resource constraints, is solved with a bidirectional dynamic programming algorithm where state labels, extension rules and dominance criteria are adapted to the problem. The authors also propose a hybrid heuristic that combines adaptive large neighborhood search

(ALNS) [47] with a local search. First, an initial solution is produced by constructing, at each iteration, a route for each vehicle type that serves unassigned customers until the transport capacity constraint is exceeded. These routes are constructed independently, which means that the same customers can be found in routes associated with different vehicle types. Then, the route of lowest cost is selected and added to the current solution. This is repeated until all customers are served. The following ALNS improvement phase explores the infeasible domain through the use of dynamically adjusted penalties that are added to the objective when constraints are violated. This ALNS follows the general guidelines provided in [50]. The removal (destroy) operators come from the literature and do not create any particular difficulty. The repair operators consist in sequential least-cost customer insertions (based on their removal order), insertions guided by a regret measure [49] or adaptations of the construction procedure for creating the initial solution. These insertion heuristics have the ability to insert recharching stations when needed. Furthermore, the vehicle type assignment can be changed if a constraint violation occurs. The cost of the vehicle type change is then added to the insertion cost. After applying the destroy and repair operators, a local search is performed on the solution obtained for intensification purposes. The local search exploits different types of neighborhoods reported in the literature where, for example, the position of a customer is changed in a route or a customer is moved from one route to another. There are also two new neighborhoods that account for the heterogeneous fleet by allowing a change to the vehicle type assignement. The *Resize* move changes the vehicle type assigned to a route without changing the route itself, while the *RelocateAndResize* tries to reduce costs by considering other vehicle type assignments for the two routes that are involved when a customer is relocated from one route to another. Finally, another procedure is applied to improve the selection and position of recharging stations in each route, given a particular order of customer visits.

Benchmark instances for the E-FSMFTW were created by extending the E-VRPTW instances in [58] with vehicle types proposed in [42] for the FSMFTW. That is, for each subset of E-VRPTW instances R1, R2, C1, C2, RC1, RC2, three to six different vehicle types are available, depending on the subset. Each vehicle type associated with a given subset has a transport capacity and three possible acquisition costs. Thus, for each original E-VRPTW instance in [58], three different instances are created depending on the chosen acquisition cost. The vehicle types in [42] also need to be extended by adding a battery capacity, battery charge consumption rate and recharging rate to obtain the final E-FSMFTW instances. The battery consumption and recharging rates are directly taken from the original E-VRPTW instances and are the same for each vehicle type. For the battery capacity, the base value is taken again from the original E-VRPTW instances but is scaled up or down, depending on the vehicle type.

The reported results first indicate that BP found the optimum of all small E-FSMFTW instances within a computation time limit set to two hours (although most instances took a few seconds; only one instance took several minutes). The hybrid ALNS also found the optimum of all small instances within one minute of computation time. On the large E-FSMFTW instances with 100 customers and 21 recharging stations, the hybrid ALNS produced solutions within one percent of the best known solutions (for each instance, the latter is identified by considering the best among the solution returned by BP, if any, and the solutions returned by ten runs of ALNS). The authors note that several of these best known solutions have been proven optimal by BP. The benefits of using a heterogeneous fleet is also quantified, by comparing the results obtained on the large E-FSMFTW instances with those obtained on the corresponding E-VRPTWs by considering only one vehicle type. These results show that substantially better solutions are produced with the heterogeneous fleet. For most of these instances, the solution does not contain only two, but three and even four different vehicle types. Also, it is observed that the number of stops to recharging stations never exceed two per vehicle on average in each subset of instances (where a subset corresponds to R1, R2, C1, C2, RC1 or RC2 plus a choice of acquisition cost). Furthermore, the best known solutions tend to have less than one stop per vehicle on average, as opposed to the corresponding E-VRPTW instances where more than one recharging station is visited on average. According to the authors, this is due to the heterogeneous fleet, since larger vehicles with more battery capacity can be used, thus leading to fewer (or no) recharging in their route.

In [46], the authors address the same problem with a multi-start heuristic made of an Iterated Local Search (ILS) [43] that interacts with a classical set partitioning (SP) formulation. In the latter, a subset of routes must be selected among all possible routes so that all customers are served exactly once. Since enumerating all routes is not possible, a restricted set of routes is considered, which is augmented through calls to the ILS. That is, the ILS generates good routes that are added to the SP formulation, which is then solved with CPLEX. On the other hand, the solutions produced by CPLEX are used as starting solutions for the ILS. The ILS uses many standard inter-route and intra-route neighborhood structures for VRPs, like the λ-interchanges [45], while the perturbation mechanism is based on multiple swap moves, including a special move that adds recharging stations to a solution. On the 168 large E-FSMFTW instances, the authors claim 76 new improved solutions over those reported in the original paper [58], particularly on instances with large fixed vehicle costs.

In [38], the authors consider a HVRP with time windows and simultaneous pick-up and deliveries, where the BEVs differ with regard to transport capacity and battery capacity. A sophisticated electricity consumption model is used that relies not only on the distance traveled by a BEV, but also on other factors like current load, rolling resistance of the road, aerodynamic drag and energy required for acceleration. The objective is to minimize the total distance traveled by the vehicles. An initial solution is first produced in a randomized way and the least-cost vehicle type is assigned to each route (which may imply the addition of one or more recharging stations). Then, a VNS is applied using different neighborhoods to improve the solution. The proposed VNS was tested on a small instance with three types of BEVs, 30 customers and 7 recharging stations.

The authors note that by increasing battery capacity, the total recharging time decreases and solution quality increases.

A HVRP with time windows motivated from a real-world package distribution company is reported in [66]. In this work, partial recharge, reuse (at most once) of vehicles and capacity constraints in weight and volume are considered. The objective accounts for fixed vehicle costs, charging costs, waiting costs and travel costs. The authors propose a greedy construction heuristic combined with VNS, where the neighborhoods are based on an increasing number of customers exchanged between routes. After all neighborhoods have been explored, a vehicle recycling operator is applied to the best found solution. Here, two routes are merged together if the arrival time of one route is earlier than the departure time of another (i.e. a vehicle will perform the two routes consecutively). Then, a departure time adjustment heuristic is applied to reduce the waiting cost as much as possible. Finally, a perturbation mechanism divides each route in three parts and exchange the middle part of different pairs of routes, before the neighborhood exploration is restarted. Test instances based on real data with 500 to 950 nodes, 100 charging stations and two different types of BEVs are considered. The results show an improvement in the order of 10% over the initial solution produced by the greedy construction heuristic. Partial recharge and reuse of vehicles allow an improvement of 5.6% and 4% in solution cost, respectively. Furthermore, the authors observe that partial recharge saves about 57.9% of the charging costs.

Table 1 summarizes the main problem characteristics considered in the above papers, that is : problem definition through a mathematical model, time windows at customer locations, presence of recharging stations, linear charging time (as defined by a charging rate), possibility of partial recharge, multiple visits at recharging stations in a vehicle route, energy consumption proportional to distance or defined through a more sophisticated model. The heading *Others* lists other characteristics that are worth mentioning: battery swap at the depot (BS), possibility of recharging at the depot (CD), multiple routes (MR) for each vehicle (i.e., reuse of vehicles) and pick-up and delivery (PD) at customer locations.

Reference	Math model	Time windows	Recharging stations	Linear charging time	Partial recharge	Multiple recharges	Energy consumption prop. to distance	Energy consumption model	Others
van Duin et al. (2013)	✓	✓					✓		BS
Lin et al. (2016)	✓		✓	✓		✓		✓	PD, CD
Hiermann et al. (2016)	✓	✓	✓	✓		✓	✓		
Penna et al. (2016)		✓	✓	✓		✓	✓		CD
Li et al. (2019)	✓	✓	✓	✓		✓		✓	PD
Zhou et al. (2021)	✓	✓	✓	✓	✓	✓	✓		MR, CD

Table 1: Characteristics of HVRPs involving only EVs

4 HVRP with EVs and ICEVs

Typically, companies do not replace their fleet of conventional vehicles by electric vehicles all at once, but progressively. Thus, it is not surprising if HVRPs with both conventional and electric vehicles have attracted the attention of researchers. To obtain high quality solutions, a good utilization trade off between the two classes of vehicles must be found, by taking into account their pros and cons. When compared to conventional vehicles, EVs are more energy efficient, have lower maintenance costs, do not emit GHGs and other pollutants and are less noisy. On the other hand, their acquisition costs are higher, they carry a smaller payload for the same vehicle weight, their limited operational range makes them dependent on the available (often scarce) recharging infrastructure with recharging times that are significant (leading to additional driver costs). Clearly, these problems are very complex, even when considering only a few of the above points. We review in the following recent work in this area.

The first paper that mentions a HVRP with BEVs and ICEVs can be found in [24]. The authors study the introduction of BEVs into the fleet of a battery distribution company. This is modeled as a pickup and delivery problem with an objective function that accounts for the vehicle fixed costs and energy consumption costs. Essentially, the authors transform the classical distance-constrained VRP (DCVRP), where the distance traveled by each vehicle cannot exceed a given limit, to obtain a time-constrained pickup and delivery problem where the recharging time, if any, is included in the total travel time of a BEV. Thus, it is assumed that BEVs can recharge anywhere and at any time when the battery capacity is exhausted (i.e., no recharging station is explicitly considered). By solving their mathematical model with CPLEX, the authors observe that the resulting solution is slightly more costly than the solution with only ICEVs, as implemented by the company, due to the high fixed costs of BEVs. However, the total distance, total travel time and number of vehicles are improved. The previously mentioned DCVRP model is directly used in [27] by conceptually associating vehicles with no distance limit to large ICEVs or PHEVs and vehicles with a distance limit to either medium or small BEVs, depending on the limit. The total distance is minimized with a metaheuristic that uses, in particular, a classical destroy-and-repair improvement phase. Two indices are also proposed to evaluate the so-called green level of a solution. These indices are based on the relative number of large, medium and small vehicles in a solution (i.e., more medium and small BEVs with regard to large ICEVs lead to a better green index).

In [37], a HVRP with time windows involving different types of vehicles (quadricycles, small vans, large vans, trucks) using different energy sources (electricity, diesel, petrol, hybrid) is considered. In this problem, EVs can only recharge at the depot. It is also possible for any vehicle to perform multiple routes within the scheduling horizon. One main feature of this work is a realistic energy consumption model for EVs, as reported in [16], that does not only depend on the distance traveled, but also on other factors like vehicle weight, rolling resistance of the road, slope of the road, aerodynamic drag and energy required for acceleration. Additional external factors, like the temperature, are also included in the final model, which allows for a more accurate estimation of the true range of each EV. The objective used in this work accounts for fixed costs, routing costs and driver costs. The problem-solving methodology is an adaptation of the sequential Clarke and Wright's savings heuristic [8]. In this sequential variant, starting from a set of individual routes (i.e., routes serving a single customer), only one route is selected and enlarged at a time by merging it, at each iteration, with the individual route that leads to the largest saving. This customer insertion process is repeated until the constraints prohibit any further customer insertion in the current route. This heuristic in integrated into a tree-based search, where a different vehicle is selected at each branch and customers are added to its route through the above sequential procedure. Results are reported on relatively small instances with at most 25 customers, using different combinations of vehicles. The authors observe that on the smallest instance with 5 customers, a single van using diesel is preferred. When the size increases to 25 customers, however, electric and hybrid vehicles appear in the best solution, thus showing their economic relevance.

In [22], a heterogeneous fleet made of ICEVs and BEVs is considered. Again, realistic energy consumption models for both ICEVs and BEVs are considered that include speed, load and slope of the road. The fuel consumption model of ICEVs is taken from [4] and is then adapted for the battery energy consumption of BEVs, based on the model in [25]. In the case of BEVs, it allows to better evaluate their electricity cost and operational range. The number of (identical) vehicles in each class are given and denoted m_E and m_{IC} for BEVs and ICEVs, respectively, with $m = m_E + m_{IC}$. The objective function accounts for the total traveled distance, fuel and electricity costs, including battery depreciation costs when applicable, and driver costs. During the proposed heuristic search, infeasible solutions are allowed by adding to the objective dynamically adjusted penalties for excess transport capacity, excess battery capacity and time window violations. At the start, m initial routes for electric vehicles are constructed through greedy insertions. In the process, recharging stations are added when a route violates battery capacity. When all customers are visited, m_{IC} long routes with strong violations of battery capacity (when the recharging stations are removed) are converted into ICEV routes. The following improvement phase is based on ALNS, enhanced with a local search for intensification purposes. The removal operators are those typically found in the literature, except for *Station vicinity removal* that removes clusters of customers close to recharging stations. The reason is that routes in these regions tend to be complex and intertwined because these visits are forced by battery capacity and time window constraints. Accordingly, it is expected that the repair operator will find a better reordering. The repair operators are based on standard greedy and regret insertions, but also include a *GRASP insertion* operator where the next customer to be inserted is not necessarily the one leading to the least additional cost, but is rather randomly chosen among the best ones stored in a candidate list. After the application of a removal and repair operator, a local seach is applied to the solution obtained, as in [29]. This local search uses standard neighborhoods for VRPs plus a special neighborhood obtained by inserting and removing visits to recharching stations. Some interesting contributions are the introduction of an adaptive mechanism into the ALNS to choose the number of customers to be removed when a solution is destroyed (similar to the adaptive selection of a removal and repair operator at each iteration) and a surrogate objective in the local search that alleviates the computational burden of calculating exactly the constraint violations of a move. More precisely, a number of best solutions in the neighborhood, based on the surrogate objective, are kept and the best solution among those, based on the true objective, is finally selected. Experiments are reported on instances derived from the PRP instances in [12]. The benchmark is made of nine sets of instances with sizes ranging from 10 to 200 customers, with 20 instances in each set. The customer locations in these instances correspond to real cities in UK, while customer demands and time windows were generated in random fashion. In this work, the speed is set to the maximum speed limit in the benchmark (i.e., 90 kms per hour) and is not a decision variable, as opposed to the load. The number of recharching stations is set to $0.1\lfloor N \rfloor$, where N is the number of customers. These stations are randomly chosen among customer locations with an additional station at the depot. The number of vehicles in the PRP solutions reported in [12] is used to set m. These vehicles are assumed to be ICEVs but are substituted with BEVs until either $m_E = \lfloor m/2 \rfloor$ or ALNS cannot find a feasible solution. The characteristics of ICEVs are taken from the PRP instances, while those of BEVs come from [11]. The authors compare the solutions obtained with vehicle load as a decision variable with those obtained with two fixed load estimates. That is, it it assumed that all vehicles are either fully loaded (worst-case estimate since it implies maximal energy consumption) or halt-loaded during their whole route. The average gaps of the solution costs obtained with these two fixed estimates, when evaluated with the actual load, were 1.89% and 1% over the solution costs obtained with a variable load. Furthermore, about a third of the solutions obtained with the half-load estimate were infeasible. The authors also indicate that the solutions differ significantly when different objectives are used. They observe that the solutions are not of high-quality when only the traveled distance is minimized, which is in line with the results in [4]. Also, they observe that BEVs have a noticeably smaller share of the total distance when only the traveled distance is minimized, because long routes are mostly assigned to ICEVs. However, the share of BEVs increases when energy costs, without battery depreciation costs, are considered because the travel costs of BEVs are cheaper than those of ICEVs. Finally, when battery depreciation costs are added, the contribution of BEVs decreases again because their travel costs become relatively expensive.

A series of papers focus on a problem involving a heterogeneous fleet of BEVs and a homogeneous fleet of ICEVs, both of fixed size, with a special consideration for recharging [52, 53, 54]. The problem is called the Heterogeneous

Electric Vehicle Routing Problem with Time-Dependent Charging Costs and a Mixed Fleet. In the problem considered, the time horizon [0, T], typically a day, is partitioned into a number of time intervals of equal duration. Also, a time T_0 is set to define the night period [0, T_0], during which vehicles are located at the depot, and a service period [T_0, T], where goods are delivered to customers. The electric vehicles have different battery capacities, transport capacities and travel costs. Three different types of chargers with different charging speeds (powers) are available at the recharging stations and not every BEV is compatible with the fastest chargers. As indicated by the problem name, the recharging costs are time-dependent to avoid energy consumption peaks. In addition, BEVs can recharge at the depot, in particular during the night, as long as the capacity of the electricity grid is not exceeded. Classical transport capacity constraints and time windows at customer locations and recharging stations are also considered. A BEV can recharge multiple times along its route and partial recharge is allowed. The objective function includes fixed costs, travel costs, charging costs and waiting costs. In [54], a two-step heuristic is proposed to address the problem. In the first step, a charging scheme is generated for the BEVs located at the depot during the night that accounts for the electricity grid and charger constraints, given that not all available BEVs can necessarily be fully charged at time T_0. This is basically a greedy heuristic aimed at minimizing the charging costs, while at the same time giving priority to BEVs with low routing costs, incompatibility with the fastest chargers and other criteria. In the second step, a joint charging and routing problem is solved during the service period [T_0, T]. First, a greedy construction heuristic is applied that considers BEVs according to their priority order. Customers are inserted into the current BEV at least additional cost. Any violation to the battery capacity is addressed by inserting a charging station into the route. When not all customers can be served by BEVs, conventional ICEVs are then considered. This construction phase is followed by a heuristic search phase, where at each iteration the solution is partially destroyed by removing a number of customers. These customers are then reinserted to identify a different, hopefully better solution. This classical destroy-and-repair approach is called Inject-Eject by the authors. After removing a randomly chosen customer and a number of nearest customers (in terms of costs), three different ways to reinsert the removed customers are compared: (1) random customer selection with cheapest insertion, (2) insertion with regret search, which is similar to (1), but allows previous insertions to be undone if it allows for a cheaper insertion of the current customer and (3) score-based insertion where the selection of the next customer is based on a score that reflects the difficulty to reinsert that customer in the current solution; this score considers, among other factors, the regret measure in [49]. The authors report results on nine real instances from two companies with 300 to 550 nodes, 18 BEVs of two different types and 8 ICEVs. They compare the three reinsertion methods and observe that the insertion with regret search provides the best results. Substantial cost improvements, in the order of 30%, are also produced by the heuristic search after the construction of the initial solution. In [53], the previous local search based on Inject-Eject moves is integrated into a multi-start ILS framework. In this case, a perturbation mechanism is applied at the end of the local search phase, which is also based on Inject-Eject moves, except that more customers are ejected from the solution. In [52], the multi-start ILS is replaced by a multi-start tabu search where a neighborhood is obtained by applying a certain number of Inject-Eject moves to the current solution. The perturbation mechanism of ILS is then used for diversification purposes within the tabu search. Tests were performed on the nine real instances mentioned above, as well as instances with 100 customers and 21 recharging stations derived from the E-VRPTW instances in [58]. In this case, the fleet is made of 50 identical ICEVs and 50 BEVs of two different types (25 BEVs of each type). The results show that the multi-start tabu search produces better solutions than the multi-start ILS for similar computation times. The improvement over the initial solution, as obtained with the best implementation of the tabu search (i.e., with the best parameter setting), is already very substantial with no restart, in the order of 50%, but the authors observe that additional significant improvements are obtained with one or two restarts.

In [55, 56], the authors address a problem with a heterogeneous fleet of BEVs and a homogeneous fleet of ICEVs, both of fixed size. A number of precomputed routes, each feasible for a BEV (in particular, with regard to the required energy), are given and must be assigned to BEVs and ICEVs. Essentially, each vehicle can perform many routes within the time horizon and can recharge at the depot between the completion of one route and the start of the next one. In this problem, the charging costs are time-dependent and the charging power delivered to a given BEV during a given time interval is a decision variable. Also, the number of available chargers is limited as well as the capacity of the electricity grid. The objective is first to maximize the traveled distance of BEVs and second to minimize their charging costs. The first objective comes from the fact that vehicles are leased and the fleet manager wants to maximize their use. A mixed integer linear programming model is first introduced and solved with CPLEX in two steps due to the lexicographic objective. Two heuristic approaches are also proposed. A sequential heuristic first considers the BEVs one by one. A number of tours are assigned to the current BEV by solving a maximum weight clique problem, where each node in the generated graph corresponds to a tour and its weight to the length of the tour. Once the tours to be performed by the BEV are determined, a charging schedule is produced with an exact algorithm (two algorithms are proposed). Afterwards, the sequential heuristic is applied to ICEVs (without the charging schedule algorithm). A two-step global heuristic is also introduced, where tours are assigned to BEVs by considering them sequentially (first step), but the charging schedules are computed for all BEVs at once at the end of the sequential assignment (second step). Computational results are reported for two real-world instances. All algorithms were able to solve the two instances at the optimum within a few seconds. The authors note that all BEVs are used in the optimal solutions and that and less ICEVs are used when compared to the existing solutions. Random instances with 40, 80, 120, 160 and 200 vehicles, with a percentage of BEVs ranging from 25% to 100% and two types of BEVs are also proposed to test the algorithms. The number of a priori computed routes is set to 1.2 or 1.3 times the number of vehicles. Depending on different parameter values, 16 classes of instances, with 10 instances in each class are generated for each number of vehicles. The authors note that CPLEX can only solve instances with 40 and 80 vehicles and that it performs better when the fleet of BEVs is homogeneous. The global heuristic was able to solve all instances whereas no feasible solution was found by the sequential heuristic for 44 instances out of 800, mostly large instances, because no feasible charging schedule was found due to its myopic behavior. Overall, the global heuristic performed the best with an average gap below 1% when compared to the best solution found by the three algorithms on each instance.

The impact of adopting alternatives to ICEVS in fleet operations is examined in [65]. The authors talk about alternative fuel vehicles (AFVs) since their approach encompasses different energy sources, like electricity, natural gas, propane, ethanol or hydrogen. Although he problem considered is motivated by service applications (e.g., technician routes for equipment maintenance), it is included in this review due to its strong similarities with delivery applications, except for service times that are substantially longer. The authors distinguish between internal service stations located at customer locations and external service stations (note that the depot is considered as an external station). In the first case, the AFV can be refueled while the technician performs the job at the customer location, and refueling stops as soon as the job is finished. So, there can be a full refuel or not. In the second case, the technician nust go to the external station and wait as long as the AFV is not fully refueled . Each vehicle route can visit service stations multiple times up to a given limit. The authors examine four different objective functions : minimize total distance, minimize total emissions, minimize total fuel costs and minimize total distance traveled by ICEVs. VNS is proposed to solve the problem. Starting with a solution obtained with only a fleet of ICEVs, AFVs are then introduced into the solution up to a number specified by the user. That is, after optimizing each route in the all-ICEVs solution, the feasibility of alternative AFV routes is considered. The set of routes is sorted in non increasing order of the saving obtained by assigning each route to an AFV. If there is not enough feasible assignments to AFVs, empty routes are created for them. Then, the VNS is applied using five standard inter-route neighborhood structures based on shift or swap of customers and a 2-opt [41]. Given that the four objectives are expressed as a weighting sum of miles traveled by ICEVs and by AFVs, the VNS is modified to also account for non dominated solutions based on these two criteria. Test instances were created by considering different numbers of customers (20, 50, 80), spatial distributions (uniform or clustered), size of service area, number of non-depot external refueling stations (0, 1, 2), number of internal refueling stations (0, 1, 2), refuel or recharge time (up to 60 minutes), AFV driving range (up to 180 miles), number of AFVs (up to six vehicles). A total of 19 different scenarios were obtained, with 10 instances in each scenario. From their experiments, the authors note that the first objective (total distance) and the fourth one (total distance traveled by ICEVs) lead to extreme solutions. In the first case, ICEVs travel the most and opportunities are missed to use AFVs, while in the second case, AFVs are so highly solicited that it leads to a substantial increase in total distance. Thus, the second objective (emissions) and the third one (fuel cost) are recommended by the authors. They also note that adding an internal service station has a more important impact on solution quality than adding an external service station. Finally, refueling time has less impact than the number of service stations or the driving range.

Other studies in the same spirit can be found in [33, 34, 35]. In [33], the authors minimize the total distance traveled either by homogeneous fleets of ICEVs (with a choice of two possible vehicle types), homogeneous BEVs (with a choice of two possible vehicle types) and heterogeneous fleets with both BEVs and ICEVs. A linear energy consumption function that accounts for load and distance is used for ICEVs and BEVs. The limited range of BEVs is introduced as a maximum distance constraint since recharging stations are not considered. ALNS is proposed to solve the problem, based on the well-known worst, random and Shaw removal operators [59] as well as different regret heuristics [49] for reinsertion. A new removal operator is also introduced to account for heterogeneous fleets. In this case, sequences of customers are removed from the current routes and reassigned, if possible, to smaller vehicles. Based on 100-customer test instances derived from Solomon's VRPTW benchmark [60], the authors observe that using heterogeneous fleets with both BEVs and ICEVs generally lead to an increase in the total distance traveled, but a decrease in CO^2 emissions, when compared to homogeneous fleets of ICEVs. However, the increase in total distance (in percentage) is much less than the decrease in CO^2 emissions. Also, the use of heterogeneous fleets allow all test instances to be feasibly solved, as opposed to fleets of homogeneous BEVs, due to their limited range and the reduced load (for the same weight) that they can carry. Finally, it is observed that the number of vehicles required to serve all customers increases when BEVs are used. In [34], which is based on a previous work reported in [35], the authors consider two optimization objectives, namely, energy minimization and travel time minimization. As in [33], a linear energy consumption function is considered that accounts for the load and distance, both for BEVs and ICEVs. A mathematical model is introduced and solved with a commercial solver. Due to this exact methodology, only small instances with at most 10 customers are addressed. In the computational tests, the authors consider homogeneous fleets of BEVs (with a choice of two possible vehicle types), homogeneous fleets of ICEVS (with a choice of two possible vehicle types) and heterogeneous fleets with both BEVs and ICEVs (with the four vehicle types), all of fixed size, based on vehicle characteristics that correspond to what is available on the market of commercial vehicles. First, no recharging station is considered and the limited range of BEVs is taken into account through a maximum distance constraint. When comparing solutions obtained with the two objectives, an important reduction in energy consumed is observed with the heterogeneous fleet when the objective function is energy minimization. The impact is much less in the case of homogeneous fleets. Increasing the battery capacity beyond that of the largest BEV type allowed some infeasible instances to become feasible, but it worsened the objective values. The authors conclude that the largest BEV type, which is available on the market, is well configured for field applications for medium- and short-distance cargo. When introducing recharging stations into the instances (and assuming that the battery is recharged at 80% of its full capacity), the authors note that these stations are seldom used and, when they are, only a small positive impact on the objective is observed, probably due to the small size of the test instances. In general, the energy consumed decreases but more time is required to perform the routes (due to the recharging time). This is true for both homogeneous fleets of BEVs and heterogeneous fleets.

In [44], a mixed fleet of fixed size of (identical) BEVs and ICEVs is considered in a problem where polluting emissions are explicitly taken into account. In the case of BEVs, electricity consumption is proportional to the distance traveled, while a fuel consumption model that also depends on the load is used for ICEVs. Fuel consumption is then used to calculate CO^2 emissions by ICEVs and the total quantity of CO^2 emissions in a solution is upper bounded. Also, there can be multiple visits to recharging stations in a route and a partial recharge is allowed. The objective includes recharging costs, activation costs (a full recharge must take place at the depot before a BEV can be used) and routing costs of BEVs and ICEVs. An ILS is proposed to solve the problem. First, two clusters of customers are constructed, one for BEVs and one for ICEVs, through an insertion heuristic. In the case of BEVs, an insertion may also require the insertion of a recharging station to satisfy the battery capacity constraints. If not all customers can be served by the available BEVs and ICEVs, these customers are assigned to ICEVs by allowing a violation of the upper bound on the total CO^2 emissions. Then, a local search is performed (with a penalty function if the initial solution is infeasible). The neighorhoods considered consist of moving nodes from one route to another. The perturbation step after the local search considers the same neighborhoods, except that worsening the solution is allowed. Test instances were created from the small E-VRPTW instances with 5, 10 and 15 customers and the large E-VRPTW instances with 100 customers in [58]. In the latter case, in addition to the original instances, the authors also consider instances obtained by selecting the first 25 or 50 customers from each original instance. By comparing the solutions obtained by ILS with optimal solutions produced by CPLEX on the small instances, it is observed that ILS finds the optimum for a majority of instances, with an average gap below 1%, when the upper bound on CO^2 emissions is larger. When the upper bound is smaller, the average gap increases to around 2%. But ILS is much faster than CPLEX in all cases. The authors also note that when the upper bound on CO^2 emissions is larger, an increased number of ICEVs is observed in the solutions when compared to BEVs, which improves the objective value, since routing ICEVs is less expensive than routing BEVs. The authors also note that allowing partial recharges provide solutions of lower cost with regard to full recharges only. On the large instances, the authors note that instances with 50 customers are solved within 2 minutes with ILS and those with 100 customers are solved within about 11 minutes. Otherwise, similar observations than those already mentioned for small instances are reported by the authors.

In [28], the authors consider a heterogeneous fleet composed of conventional ICEVs, BEVs and PHEVs. Although PHEVs do not suffer from the operational range restrictions of BEVs, the presence of two engines lead to a heavier vehicle with an associated higher consumption of electricity and fuel. The problem addressed by the authors is called the hybrid heterogeneous electric fleet routing problem with time windows and recharging stations (H^2E-FTW). Within each one of the three classes of vehicles, that is ICEVs, BEVs and PHEVs, different vehicle types are defined that differ in acquisition cost, transport capacity, battery capacity and electricity and/or fuel consumption rates. A sum of fixed and variable routing costs is to be minimized. Fixed costs correspond to vehicle acquisition, vehicle maintenance and driver costs, while routing costs correspond to the quantity of electricity and fuel consumed, weighted by their respective costs. The proposed methodology takes into account vehicle characteristics only in the route evaluation procedure, thus allowing a state-of-the-art metaheuristic, namely the Hybrid Genetic Algorithm (HGA) [64], to be applied at the upper level on a simpler abstraction of the problem. The evaluation of a route, represented as a sequence of customers with the corresponding vehicle type, consists of two layers. The first layer solves a resource-constrained shortest path problem using dynamic programming to insert recharging stations into the routes. Then, the second layer optimizes the recharge level at each station, the engine mode choice (when applicable) and visit times. At the upper level, HGA uses a recombination operator that works on a giant-tour representation of the routes and a mutation operator based on a destroy-and-recreate procedure. The best routes produced during the search are stored in memory and, at regular intervals, a set partitioning procedure is also applied to produce a solution by combining a subset of those routes. The solution produced at each iteration with recombination, mutation, or set partitioning is finally improved with a local search. Test instances for the problem were generated from the E-VRPTW instances with 100 customers and 21 recharging stations in [58]. Each instance was extended by adding vehicle types for each class with characteristics taken from [48] for a total of nine vehicle types, that is, three vehicle types for each class. The results show that the operational cost of the best mixed fleet can be 7% lower than the best homogeneous fleet made either of ICEVs, BEVs or PHEVs. The authors also compare their method on benchmark instances of the E-VRPTW [58], E-VRPTW with partial recharge [31] and E-FSMFTW [29], a related heterogeneous fleet size and mix problem with fixed costs that considers only BEVs with full capacity recharging. For the first two problems, the proposed algorithm produces results similar to those reported in the literature with an average gap of 0.2% with the best known solutions. For the E-FSMFTW, new best solutions are found for 119 out of the 168 benchmark instances reported in [29].

Table 2 summarizes the main characteristics of the problems considered above, that is : problem definition through a mathematical model, time windows at customer locations, presence of recharging stations, fixed charging time, linear charging time, possibility of partial recharge, multiple visits at recharging stations in a vehicle route, energy consumption proportional to distance or defined through a more sophisticated model. The heading *Others* lists other characteristics that are worth mentioning: possibility of recharging at customer locations (CC), possibility of recharging at the depot (CD), multiple charging technologies (MT), multiple routes (MR) for each vehicle, pick-up and delivery (PD) at customer locations, time-dependent charging costs (TD), time windows at recharging stations (TW) and presence of hybrid vehicles (HV).

5 Conclusion

This work has reported the state-of-the-art on heterogeneous vehicle routing problems involving electric vehicles for delivery applications. This area has attracted a growing interest due to the progressive replacement of conventional vehicles by electric vehicles in commercial fleets. This research is still in its infancy and further studies are required to better understand the impact of the objective function, routing constraints and electric vehicle characteristics on the right mix of vehicles. In this regard, multi-objective optimization is an alternative that can be better exploited by researchers to provide useful insights to decision makers. The impact of EVs on other complex VRP variants have also been overlooked, for example, multiple depots, time-dependent travel times and location-routing, where both the location of recharging stations and the routing of electric vehicles are considered (but, see the recent work in [7]). Uncertainty, which can be addressed through stochastic optimization, has always been a pervasive issue in vehicle routing (demand, travel time). It now encompasses other issues related to characteristics of BEVs, like their driving range. Finally, only a few works consider the integration of HEVs or AFVs, for example hydrogen powered vehicles, into fleets of vehicles. Even if a lot of energy is lost during the production of hydrogen and its conversion to electricity, it might still be indicated for large trucks in medium to long-distance applications.

New emerging trends in the field of EVs must also be integrated into HVRP studies. One example is regenerative breaking that allows the electric engine to store charge while the vehicle is going downhill. More generally, developments related to dynamic charging (which allows a vehicle to recharge while being in movement) are worth considering in the future.

Reference	Math model	Time windows	Recharging stations	Fixed charging time	Linear charging time	Partial recharge	Multiple recharges	Energy consumption prop. to distance	Energy consumption model	Others
Gonçalves et al. (2011)	✓			✓			✓	✓		PD
Goeke and Schneider (2015)	✓	✓	✓		✓		✓		✓	
Lebeau et al. (2015)	✓	✓			✓				✓	CD, MR, HV
Sassi et al. (2015)	✓		✓		✓	✓	✓	✓		CD, MT, TD, TW
Kopfer and Schopka (2016)	✓	✓							✓	
Sassi and Oulamara (2017)	✓				✓	✓		✓		CD, MR, TD
Yavuz and Çapar (2017)	✓		✓		✓	✓	✓	✓		CD ,CC
Kopfer and Vornhusen (2019)	✓	✓	✓	✓			✓		✓	
Hiermann et al. (2019)		✓	✓		✓	✓	✓	✓		HV
Macrina et al. (2019)	✓	✓	✓		✓	✓	✓	✓		MT
Hatami et al. (2020)	✓									

Table 2: Characteristics of problems involving both conventional vehicles and EVs

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