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A GRASP with penalty objective function for the Green Vehicle Routing Problem with Private Capacitated Stations

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Abstract

Due to the recent worries about the environment, the transportation companies are incentivized to use *Alternative Fuel Vehicles* (AFVs) instead of the conventional ones. However, due to the limited AFV driving range and since the *Alternative Fuel Stations* (AFSs) are usually not widespread on the territory, the routes of AFVs have to be properly planned in order to prevent them from remaining without the sufficient fuel to reach the depot or the closest station. The *Green Vehicle Routing Problem* (G-VRP) aims at determining the AFVs routes, each one serving customers within a maximum duration, minimizing the total travel distance and, if necessary, including stops at AFSs. Contrary to G-VRP, *G-VRP with Capacitated AFSs* (G-VRP-CAFS) more realistically assumes that each AFS has a limited number of fueling pumps and therefore prevents overlapping in refueling operations. In this paper, we propose a *Greedy Randomized Adaptive Search Procedure* (GRASP), which properly uses some theoretical results and efficiently solves large-sized instances of G-VRP-CAFS. Computational results carried out on both benchmark instances and large-sized instances show the effectiveness and the efficiency of the proposed GRASP.

Keywords: Routing, Metaheuristics, Greedy Randomized Adaptive Search Procedure, Alternative Fuel Stations, Route Incompatibility

1. Introduction

According to a recent report published by the European Environment Agency, about 25% of the total greenhouse gas emissions in Europe is due to the transportation sector (Agency (2020)). Therefore, cutting emissions due to this sector plays a key role in order to reach one of the long-term

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goals of the European Union, i.e., having net-zero greenhouse gas emissions by 2050. Indeed, instead of the traditional Internal Combustion Engine Vehicles (ICEVs), the European Union is currently incentivizing Alternative Fuel Vehicles (AFVs) that use alternative fuel like, for instance, biodiesel, electricity, hydrogen. As a consequence, many companies operating in the logistics sector are currently considering either replacing or integrating their fleet with AFVs.

Compared to ICEVs, AFVs guarantee several advantages among which less global harmful emissions (*environmental sustainability*) and lower kilometer costs (*economic sustainability*). In addition, they can also reach the so-called Limited Traffic Zones, typically forbidden to ICEVs. As a result, they guarantee both a widespread customers coverage especially in last-mile Logistics and a more efficient door-to-door transportation (*social sustainability*). However, despite these benefits, AFVs have usually a limited driving range and, therefore, they may require refueling more than once during a trip. In addition, Alternative Fuel Stations (AFSs) are currently not widespread on the territory and this implicitly requires to properly plan the route of such vehicles in order to avoid that they may remain without the sufficient fuel level to reach the closest station.

In fact, it is not surprising if a growing number of operations research specialists are currently studying the problem of efficiently routing a fleet of AFVs, i.e., the *Green Vehicle Routing Problem* (G-VRP). G-VRP was introduced by the seminal work of Erdoğan and Miller-Hooks (Erdoğan & Miller-Hooks (2012)). Compared to the traditional *Vehicle Routing Problems* (VRPs), this problem takes into account also the need of the fleet to refuel during the trips and then, it includes stops at AFSs. The route of each AFV of the fleet starts from a common depot and returns to it within a maximum time duration. During its route, an AFV serves some customers, each one with a specific service time, possibly stopping at stations to refuel. Since the fuel consumption rate is assumed to be proportional to the travelled distance, the driving range of each AFV can be easily deduced from its tank capacity. Moreover, the refueling time at each station is assumed to be constant. Therefore, G-VRP aims at routing a set of AFVs to serve customers geographically distributed with possible stops at AFSs, minimizing the total travel distance.

Starting from Erdoğan & Miller-Hooks (2012), an increasing number of scientific contributions have been published in the literature, addressing either the original G-VRP or its variants. In almost all these contributions, each AFS is assumed to have an unlimited number of fueling pumps and therefore, each AFV always fuels at a station without waiting. Clearly, this assumption does not hold in real-life applications, where each AFS has instead a limited number of fueling pumps. Only in 2019, Bruglieri, Mancini and Pisacane introduced G-VRP with Capacitated AFSs (G-VRP-CAFS), i.e., G-VRP, in which the stations have a limited number of fueling

pumps (Bruglieri et al. (2019b)). The same authors also showed how the AFS capacity becomes a bottleneck in some particular situations, in which several AFVs may overlap at the same AFS during the refueling operations. Compared to Bruglieri et al. (2019b), in this paper, we focus on the private scenario, in which AFSs are only those owned by the company. The main contributions of this work are listed in the following:

- the design and the implementation of a metaheuristic solution approach suitable to efficiently address G-VRP-CAFS allowing route duration infeasibility in the starting solution and eliminating it along the search through a penalty objective function;
- the set up and proof of some theoretical results about the compatibility among routes, properly used by the proposed metaheuristic approach;
- the generation of a new and more realistic set of benchmark G-VRP-CAFS instances with a significant number of customers to serve.
- a sensitivity analysis of the move performances used in the metaheuristic and on the number of AFVs used increasing the station capacity

The rest of the paper is organized as follows. Section 2 presents an overview of the main contributions in the literature. Section 3 describes the problem addressed and the notation used. Section 4 provides some theoretical results. Section 5 describes the solution approach. Section 6.1 details the instances generation procedure and Sections 6.2 and 6.3 discuss the experimental results. Finally, Section 7 draws some conclusions and outlines some future research directions worthy of investigation.

2. Related Work

G-VRP belongs to the class of VRPs (see, e.g., Toth et al. (2015)). It is an interesting problem, currently attracting the interest of many operations research specialists, as shown in several recent surveys, e.g., Bektaş et al. (2016), Bektaş et al. (2019), Asghari et al. (2020), Moghdani et al. (2020). Introduced in Erdoğan & Miller-Hooks (2012), it is mathematically modeled through Mixed Integer Linear Programming (MILP) by cloning the stations in order to allow multiple visits to the same station. The need of cloning the stations makes this formulation not suitable to be used on real-life alike instances. For this reason, a Clarke & Wright Savings like algorithm, properly modified for G-VRP, is also proposed.

A first attempt to get rid of AFS clones is described in Koç & Karaoglan (2016), where a three-index MILP model is proposed, through variables indicating if an AFV stops at an AFS traveling from a node to another. The authors propose a Branch&Cut exact algorithm that combines several valid inequalities and a Simulated Annealing (SA) based approach to obtain upper

bounds. Also in the MILP cloneless formulation proposed in Bruglieri et al. (2016), the stops at AFSs are only implicitly considered. But, compared to Koç & Karaoglan (2016), the number of variables is significantly reduced by pre-computing a set of efficient AFSs for each pair of customers. The problem of avoiding AFS clones is addressed in Bruglieri et al. (2019c), where two MILP models are proposed. In the first one, between two customers or between a customer and the depot, only one stop at an AFS is allowed. On the contrary, in the second model, two consecutive stops at AFSs are also allowed. The same paper also describes valid inequalities and dominance criteria to a priori identify AFSs that are more efficient to use in each route. Finally, in Leggieri & Haouari (2017), an MILP formulation is proposed together with a reduction procedure, shown to be competitive on medium-sized instances.

An exact solution approach, based on the definition of a multigraph, is proposed in Andelmin & Bartolini (2017). In particular, each node is a customer whereas an arc between two nodes is a nondominated path that may include also stops at AFSs. The set of routes found on the multigraph is the input of a set partitioning model strengthened through valid inequalities. The authors optimally solve instances with up to 100 customers. A path-based exact solution approach is proposed in Bruglieri et al. (2019a), where the authors exploit both the limited driving range of AFVs and the maximum route duration. In particular, a path represents an ordered sequence of customers, visited from a starting node to an ending node without intermediate stops at any AFS. The number of all exhaustively generated paths is properly reduced by both feasibility and dominance conditions. The set of all feasible non-dominated paths is finally given as input to a path-based model for building the optimal solution. The proposed approach outperforms all exact solution methods already existing on both small and medium-sized instances. On large-sized instances, the set of feasible non-dominated paths is instead heuristically generated.

Regarding meta-heuristics designed for G-VRP, the one proposed in Montoya et al. (2016) consists of two stages. In the first stage, a pool of routes is generated through some randomized route-first cluster-second heuristics and a properly designed AFSs insertion procedure. In the second stage, this pool becomes input of a set partitioning formulation. A Genetic Algorithm (GA) is instead proposed in da Costa et al. (2018), tested on real-world instances including road speed and gradient data. Whereas, in Affi et al. (2018), a Variable Neighborhood Search (VNS) is designed and shown to be competitive on large-sized benchmark instances. The multi-start local search algorithm described in Andelmin & Bartolini (2019) uses the multigraph reformulation proposed in Andelmin & Bartolini (2017). The solutions iteratively built are improved by a local search and all these routes are input of a set partitioning model. The final solution is further improved through a local search.

Variants of the problem include, for instance, G-VRP with Pickups and Deliveries (G-VRPPD). For example, Madankumar & Rajendran (2018) model the problem of minimizing costs, considering pickup and delivery operations, product and vehicle compatibility, vehicle capacity, request-priorities and request-types as well as start/completion time constraints. A second model is also proposed considering different fuel prices at different AFSs, with the objective of minimizing both routing and refueling costs. A G-VRPPD is also addressed in Soysal et al. (2018). In particular, compared to the models traditionally proposed for the one-to-one pickup and delivery problem, in this paper, new aspects are considered, such as fuel consumption, variable vehicle speed and road categorization (i.e., urban, non-urban). The resulting problem is modeled through MILP and solved on a case study from the Netherlands. A bi-objective Fuel G-VRP with varying speed constraint is discussed in Poonthalir & Nadarajan (2018). The problem is modeled through goal programming for minimizing route cost and fuel consumption and is solved by Particle Swarm Optimization with greedy mutation operator and time varying acceleration coefficient. In Zhang et al. (2018), G-VRP with vehicle capacity constraint is addressed and a two-phase heuristic and an Ant Colony based meta-heuristic are designed. In Xu et al. (2019), together with the vehicle capacity constraint, G-VRP with time-varying vehicle speed and soft time windows is modelled through multi-objective Mixed Integer NonLinear Programming and solved through a non-dominated sorting GA with adaptive and greedy strategies. In Hooshmand & MirHassani (2019), it is assumed that the travel time and the fuel consumption on each arc depend on the distance traveled and the time of the day at which that arc is traversed. The problem is then modelled through MILP and solved by a hybrid heuristic on large-sized instances. In Yu et al. (2019), a Branch&Price algorithm is designed to solve G-VRP with heterogeneous fleet and time windows. For such a variant, a labeling based multi-vehicle approximate dynamic programming algorithm is developed. A G-VRP with Time Windows is studied in Yu et al. (2020) where an Adaptive Large Neighborhood Search (ALNS) is proposed.

Some papers assume that the green fleet specifically consists of Electric Vehicles (EVs). Electric VRP with Time Windows (E-VRPTW), introduced in Schneider et al. (2014), is more difficult than G-VRP since the recharging time depends on the actual battery level. E-VRPTW is formulated by MILP and a hybrid heuristic combining a VNS with a Tabu Search is also proposed for solving large-sized instances. After that, an increasing number of works addresses E-VRPTW and its variants. For example, in Felipe et al. (2014), the amount of energy recharged and the technology used are both taken into account together with the route plan. Constructive and local search heuristics are then designed and embedded into a non deterministic SA. E-VRPTW with partial recharges is introduced in Bruglieri et al. (2015), assuming that an EV is not always fully recharged at a sta-

tion. This way, the battery level recharged each time becomes a decision variable. For this variant, an MILP formulation is proposed, minimizing the total travel time, the total waiting time and the total recharging time plus the number of EVs used. A VNS Branching (VNSB) metaheuristic is designed in order to solve also large-sized instances in reasonable computational times. Considering partial recharges, an ALNS is designed and described in Keskin & Çatay (2016). Four variants of E-VRPTW are instead addressed in Desaulniers et al. (2016), i.e., with either at most a single or multiple recharges per route, with either full or partial recharges. For these variants, Branch&Price&Cut algorithms are proposed. Recently, in Ceselli et al. (2021), an EVRP with multiple recharge technologies is addressed and solved through a Branch&Cut&Price algorithm. In particular, in the master problem, each column is a sequence of customers visited between two stations. The proposed algorithm is suitable to solve instances with up to thirty customers, nine recharge stations, five vehicles and three technologies. In Bruglieri et al. (2017), a VNSB is used in a three-phase framework for addressing E-VRPTW with partial recharges. In particular, the number of EVs used is firstly optimized and then, the total time spent by EVs, i.e., travel, charging and waiting times, is minimized. In the first two phases, MILP-based Programs are used to generate feasible solutions, input of the VNSB. In Keskin & Çatay (2018), E-VRPTW with partial recharges is addressed considering a normal, a fast and a super-fast recharging configuration. The total recharging cost while operating, minimum number of vehicles is minimized. An MILP model is then proposed and solved on small-sized instances while the large-sized instances are solved by applying an ALNS. EVs are instead used for both pickup and delivery operations in Goeke (2019). The author designs a metaheuristic to solve the problem and derives a policy determining the energy to be recharged in the case of time windows. In Lu et al. (2020), the time-dependent EVRP is addressed in which together with the routes plan, decisions on vehicle speed and departure time at each arc of the routes have to be also taken for minimizing a cost function. This problem is modelled through ILP and solved by an iterated VNS on more realistic instances. Finally, in Montoya et al. (2017), non-linear charging functions are assumed in contrast with traditionally made assumption according to which the battery-charge level is a linear function of the charging time. For this variant, a hybrid metaheuristic is designed.

In Poonthalir & Nadarajan (2019), G-VRP is addressed assuming that, in some cases, AFVs have to wait before being refuelled. For this reason, each AFS is modelled as an M/M/1 queue. This new variant is then solved through Chemical Reaction Optimization. In Keskin et al. (2019), E-VRPTW is addressed considering waiting times at stations and a time horizon split into intervals with varying queueing times. An ALNS combined with an exact method based on the solution of an MILP model is proposed. The same authors in Keskin et al. (2020) formulate the problem

as a two-stage model. In the first stage, expectations of queueing times are used to detect routes by the ALNS. In the second stage, these routes are corrected via simulation.

To the best of our knowledge, only in Bruglieri et al. (2019b), G-VRP-CAFS is addressed without queueing at AFSs. In particular, two different scenarios are considered. In the private scenario, AFSs are owned by the transportation company and therefore, stops at them are properly managed without overlapping among AFVs. In the public scenario, instead, AFSs are not owned by the transportation company and a fueling pumps reservation mechanism is considered in order to prevent AFVs queueing at stations. As a consequence, time windows associated with AFSs availability are introduced. For both the scenarios, arc-based MILP formulations are proposed. Moreover, the path-based approach of Bruglieri et al. (2019a) is also extended for this new variant. In particular, for efficiently solving the path-based models, two cutting-plane exact approaches are also designed. The exact solution approaches are nevertheless suitable to solve only middle-sized instances.

In the present work, starting from the aforementioned assumptions holding in the private scenario, an efficient and effective metaheuristic method is described in order to also address large-sized instances of G-VRP-CAFS.

3. Problem Statement and Notation

In this section, we recall the problem statement, the notation and the assumptions already introduced in Bruglieri et al. (2019b), as also summarized in Table 1.

G-VRP-CAFS is defined on a direct complete graph $G = \langle N, A \rangle$ where $N = I \cup F \cup \{0\}$ denotes the set of nodes containing the set of customers I to serve, the set of private AFSs F and the common depot 0. Set A contains all the arcs (i, j) such that $i, j \in N$ and $i \neq j$.

The number of AFVs available is an input data, indicated by m . Moreover, the maximum route duration as well as the maximum distance an AFV can travel after a full refueling are denoted by T_{max} and D_{max} , respectively. In addition, v , Q and r indicate the average vehicle speed, the vehicle fuel capacity and the fuel consumption rate, respectively. This way, the parameter D_{max} can be easily computed as $D_{max} = \frac{Q}{r}$. Moreover, each AFV has an unlimited cargo capacity. In addition, since all AFVs start from the depot fully refueled, an initial refueling time p^{start} is also introduced to take into account the time spent for the initial refueling. Furthermore, only one refueling is assumed to be allowed between two customers.

For each customer $i \in I$, a service time p_i is given. For each AFS $s \in F$, both a constant refueling time p_s and the number of fueling pumps η_s are known. For each pair of nodes $i, j \in N$, a travel distance d_{ij} as well as a travel time t_{ij} are known.

Table 1: Nomenclature of G-VRP-CAFS

Notation	Meaning
F	Set of AFSs
I	Set of customers
N	Set of nodes
A	Set of arcs
p^{start}	Initial refueling time
m	Number of available AFVs
0	Depot
v	Average speed
Q	Maximum fuel capacity
r	Fuel consumption rate
T_{max}	Maximum route duration
D_{max}	Maximum driving range
p_s	Refueling time $\forall s \in F$
η_s	Number of fueling pumps $\forall s \in F$
p_i	Service time $\forall i \in I$
d_{ij}	Travel distance $\forall (i, j) \in A$
t_{ij}	Travel time $\forall (i, j) \in A$

G-VRP-CAFS consists in finding at most m routes, starting and ending in the depot, such that all the customers are served and the maximum route duration, the driving range after a refueling and the AFS capacity are never exceeded. The objective is the minimization of the total traveled distance.

4. Some Theoretical Results

A question that frequently must be addressed when G-VRP-CAFS is solved with a metaheuristic approach is whether two routes, refueling at the same AFS, are compatible, i.e., they can be scheduled in such a way that they do not overlap when refueling.

To this purpose, for each route we can compute the earliest visit time of each node and the maximum shifting that does not violate T_{max} (i.e., the difference between T_{max} and the minimum route duration). The question is solved by the following proposition, when the station capacity is 1.

Proposition 4.1. *Two routes ω_1 and ω_2 , refueling at the same AFS s with capacity $\eta_s = 1$, are incompatible if and only if the following two conditions simultaneously hold:*

$$\tau_1 + p_s - \tau_2 > \sigma_2 \quad (1)$$

$$\tau_2 + p_s - \tau_1 > \sigma_1 \quad (2)$$

where τ_1 and τ_2 are the earliest visit time of station s in the routes ω_1 and ω_2 , respectively, with $\tau_1 \leq \tau_2$, and σ_1, σ_2 their maximum shifting.

Proof. ($\Leftarrow$) Suppose that the two inequalities hold. From $\tau_1 + p_s - \tau_2 > \sigma_2$ we deduce $\tau_1 + p_s > \tau_2$ and therefore the earliest refueling start time of ω_2 overlaps with the earliest refueling ending time of ω_1 . Moreover, it is not possible to postpone the refueling start time of ω_2 when the refueling of ω_1 is finished, since in this case ω_2 should be postponed by $\tau_1 + p_s - \tau_2$ that exceeds its maximum allowed shifting σ_2 because of inequality (1). On the other hand, if we postpone the refueling of ω_1 starting it when the refueling of ω_2 is ended, then the shifting of ω_1 would be $\tau_2 + p_s - \tau_1$ violating its maximum allowed shifting σ_1 due to inequality (2).

($\Rightarrow$) Suppose that ω_1 and ω_2 are incompatible. If inequality (1) is not satisfied, then it would be possible to postpone the refueling start time of ω_2 immediately after the refueling ending time of ω_1 (given by $\tau_1 + p_s$) without exceeding its maximum allowed shifting since $\tau_1 + p_s - \tau_2 \leq \sigma_2$. In a similar way, if inequality (2) is not satisfied, then it would be possible to postpone the refueling start time of ω_1 immediately after the refueling ending time of ω_2 (given by $\tau_2 + p_s$) without exceeding its maximum allowed shifting since $\tau_2 + p_s - \tau_1 \leq \sigma_1$. Hence, both the conditions (1) and (2) are necessary for the incompatibility. $\square$

According to Proposition 4.1, the compatibility of two routes sharing an AFS with capacity 1 can be checked in polynomial time just verifying that at least one between inequalities (1) and (2) is violated. More in general, if the routes are m , in order to establish if they are compatible or not, we have to proceed as follows. First of all, we order the routes by increasing earliest visit time of the shared station. If a route and the next one satisfy the inequalities (1) and (2), then the two routes are incompatible and we stop. Otherwise, if only one of the two inequalities is violated and the two routes overlap while refueling, then only one of the two routes, $\bar{\omega}$, can be postponed in feasible way to avoid to overlap the other route while refueling. Then, in this case, its refueling start time $\tau_{\bar{\omega}}$ and its shifting $\sigma_{\bar{\omega}}$ is updated, as well as its position in the ordered list of the routes by increasing visit time of the shared station. Otherwise, if both inequalities (1) and (2) are violated and the two routes overlap while refueling, then the overlap can be avoided in two feasible ways: by postponing the refueling start time either of the first route or the second one. If making one of the two choices we arrive to an infeasibility (i.e. both (1) and (2) are satisfied), we have to backtrack to check if, with the alternative choice, the infeasibility can be avoided. If all the routes have been checked without detecting infeasibility, we stop stating that the m routes are compatible.

We observe that Proposition 4.1 is also useful when a station has a capacity greater than 1, e.g. 2, and the routes passing through this shared station are $m > 2$. Indeed, as soon as a pair of incompatible routes is found (i.e., they satisfy (1) and (2)), then the two routes must necessarily refuel on 2 different pumps and then we must verify that none of the $m - 2$ remaining

routes are incompatible simultaneously with both the route refueling at the first pump and the one refueling at the second pump.

Hereafter, we call $Reschedule(r_1, \dots, r_m)$ the procedure that allows checking if a given set of m routes can be scheduled in such a way that the capacity of the shared station is not violated. This procedure returns *false* if the routes are incompatible, otherwise it adjusts the visit time of the shared AFS in such a way that AFVs do not overlap when refueling in the shared AFS.

5. A Greedy Randomized Adaptive Search Procedure for the G-VRP-CAFS

GRASP has been introduced in Feo & Resende (1989). It is a multi-start metaheuristic, widely applied to a large set of problems, including facility location Ferone et al. (2017), scheduling González-Neira et al. (2017), constrained shortest path Ferone et al. (2016), and vehicle routing problems Nguyen et al. (2012); Haddadene et al. (2016). For an extensive survey, the reader is referred to Festa & Resende (2002, 2009a,b).

Each GRASP iteration is characterized by two main phases: construction and local search. Starting with an empty solution, the construction phase iteratively adds an element, one at a time, until a complete solution is obtained. The elements that can be added to the solution make up the *Candidate List* (CL). Elements are sorted according to some greedy function, that measures the benefit of selecting each of them. Then, the construction phase creates the *Restricted Candidate List* (RCL) selecting the best elements of CL with respect to the greedy function. At the end, an element is randomly selected from the RCL and added to the solution under construction. The aim of the local search is to improve the solution generated by the construction phase, returning a locally optimal solution with respect to some neighborhood structure. The pseudo-code of a generic GRASP for a minimization problem is reported in Algorithm 1.

Algorithm 1: Pseudo-code of a generic GRASP.

Output: Best found solution sol^* .

```

1  $sol^* \leftarrow \text{NIL};$ 
2  $\text{cost}(sol^*) \leftarrow +\infty;$ 
3 while a stop criterion is not met do
4   Build a greedy randomized solution  $sol$  ;
5    $sol \leftarrow \text{LocalSearch}(sol)$  ;
6   if  $\text{cost}(sol) < \text{cost}(sol^*)$  then
7      $sol^* \leftarrow sol;$ 
```

5.1. Construction phase

In our proposal, the construction phase iteratively adds a route at a time until all customers are served or it is not possible to serve the remaining ones. The pseudo-code of the construction phase is reported in Algorithm 2, where $\oplus$ denotes the concatenation operator.

Algorithm 2: Pseudo-code of the construction phase.

Input: The set of not served customers UC ;
Input: Non-symmetric distribution function D .
Output: Solution sol .

```

1  $sol \leftarrow \emptyset$ ;
2 do
3    $added \leftarrow \text{false}$ ;
4    $r \leftarrow [0]$  ;
5   while true do
6      $CL \leftarrow \text{getReachableLocations}(UC, r)$  ;
7     if  $CL = \emptyset$  then break ;
8     Randomly select  $i \in \{1, \dots, |CL|\}$  according to distribution
        $D$  ;
9      $r \leftarrow r \oplus [CL_i]$  ;
10     $UC \leftarrow UC \setminus \{CL_i\}$ ;
11     $added \leftarrow \text{true}$ ;
12   $r \leftarrow r \oplus [0]$  ;
13  if  $added$  then  $sol \leftarrow sol \cup \{r\}$ ;
14 while  $added$ ;
15 Reschedule( $sol$ )

```

At each iteration, a new route is initialized with the depot (line 4). Then, the set of reachable locations is computed (line 6), and a location is randomly selected and added to the route (lines 8–9). When the set of reachable locations is empty, the route ends (lines 7 and 12). It is duly to note that we used the biased-randomized selection proposed in Ferone et al. (2019). Typically, the next element to be added to the partial solution is randomly selected from the RCL with a uniform distribution. In our case, we use a non-symmetric distribution that is biased towards the most promising solution elements.

A crucial aspect of the construction phase lies in the function that returns the set of reachable locations, i.e., `getReachableLocations`. Let d_r and τ_r be the travel distance since the last refueling and the total travel time of the partial route r , respectively. Moreover, let i be the last node of the partial route r , then we define the following four sets.

- Set L_1 of all the unserved customers that can be served returning

to the depot without violating the constraints on both the maximum distance travelled without refueling D_{max} and the maximum route duration T_{max} . Formally,

$$L_1 = \left\{ c \in UC \mid \begin{array}{l} d_r + d_{ic} + d_{c0} \leq D_{max}, \\ \tau_r + t_{ic} + p_c + t_{c0} \leq T_{max}. \end{array} \right\}$$

- Set L_2 of all the unserved customers that can be served returning to the depot after visiting a fueling station:

$$L_2 = \left\{ c \in UC \mid \exists s \in F: \begin{array}{l} d_r + d_{ic} + d_{cs} \leq D_{max}, \\ \tau_r + t_{ic} + p_c + t_{cs} + p_s + t_{s0} \leq T_{max}. \end{array} \right\}$$

- Set L_3 of fueling stations that can be used to serve a customer respecting the constraints on both the maximum driving range and the maximum route duration:

$$L_3 = \left\{ s \in F \mid \exists c \in UC: \begin{array}{l} d_r + d_{is} \leq D_{max}, \\ d_{sc} + d_{c0} \leq D_{max}, \\ \tau_r + t_{is} + p_s + t_{sc} + p_c + t_{c0} \leq T_{max}. \end{array} \right\}$$

- Set L_4 of fueling stations that can be used to come back to the depot:

$$L_4 = \left\{ s \in F \mid \begin{array}{l} d_r + d_{is} \leq D_{max}, \\ \tau_r + t_{is} + p_s + t_{s0} \leq T_{max}. \end{array} \right\}$$

If route r contains an AFS, the set of reachable locations L is equal to L_1 . Otherwise, L is defined as $L = \bigcup_{i=1}^4 L_i$. All the locations $l \in L$ are sorted in non-decreasing order with respect to the distance d_{il} , and the greedy criterion prefers the shortest ones.

It is worth noting that AFVs do not refuel only when necessary. This way, we want to avoid a situation where several vehicles may refuel at near times at the same station violating its capacity. Finally (line 15), the function *Reschedule*, introduced in Section 4, tries to schedule the routes of the solution *sol* in such a way that they do not overlap when refuel in the same AFS. If it is not possible, the overlap is still prevented by postponing the refueling of the shortest route, for each pair of incompatible routes, even if the maximum route duration T_{max} is violated. The route duration infeasibility is managed along the search procedure as explained in detail in Section 5.3.

5.2. Local search

Each GRASP iteration entails a local search as intensification phase. Generally, given a neighborhood function N , this procedure looks for a local optimum with respect to N . Since during the years, several neighborhood

functions have been proposed for routing problems, we adapted some of them to our problem.

In particular, as local search we used a Variable Neighborhood Descent (VND) approach whose pseudo-code is reported in Algorithm 3. For each $h = 1, \dots, h_{\max}$, the h -th neighborhood of solution sol is explored obtaining a solution sol' . If the cost of sol' is lower than the cost of sol , then sol' replaces sol and the procedure restarts by exploring the first neighborhood of the new solution sol ; otherwise, it continues by exploring the $(h+1)$ -th neighborhood of sol . The local search stops when all the neighborhoods have been explored without improving the current incumbent solution. Consequently, the final solution is a local optimum with respect to all $h_{\max}$ neighborhoods.

Algorithm 3: Pseudo-code of VND.

Input: Solution sol

Output: Improved solution sol

```

1  $improved \leftarrow 1$  ;
2 while  $improved = 1$  do
3    $h \leftarrow 1$  ;
4    $improved \leftarrow 0$  ;
5   while  $h \leq h_{\max}$  do
6      $sol' \leftarrow N_h(sol)$ ;
7     if  $cost(sol') < cost(sol)$  then
8        $sol \leftarrow sol'$ ;
9        $improved \leftarrow 1$ ;
10       $h \leftarrow 1$  ;
11    else
12       $h \leftarrow h + 1$ ;
13 return  $sol$  ;
```

In the next sections, we analyze the neighborhoods used in the local search that have been used by VND in the same order as they are listed in the following.

5.2.1. Change station

Figure 1 depicts the first move used in VND. It consists in changing the used fuel stations. All the routes in the solution are examined, and for each pump used of each visited AFS s , the procedure firstly checks if it is possible to replace a pump with another one of the same station; otherwise, if it is possible to replace s with another station s' . In this case, the route is modified by inserting s' at the place of s . We remark that the dominated stations are not removed since they may be useful to guarantee that a solution is feasible with regard to the station capacity.

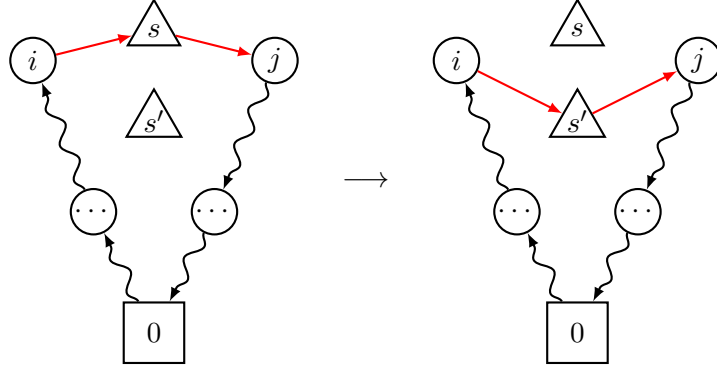


Figure 1: Change station move.

5.2.2. Destroy route

The second neighborhood structure consists in destroying a route and inserting its customers in the remaining routes. For each customer, the best insertion position in terms of solution quality is found. During the local search, the move is applied for each route, and the best found solution is selected. It is worth noting that this operator helps to restore solution feasibility on the maximum number of AFVs that can be used, constraint that we are relaxing through the penalty function.

5.2.3. 2-Opt

2-Opt is a classical neighborhood structure for routing problems, and the main idea behind it is to take a route that crosses over itself and reorder it so that it does not. An example is given in Figure 2. For each route, all possible pairs of arcs are examined, and if there exists at least one improving swapping, the best one is performed.

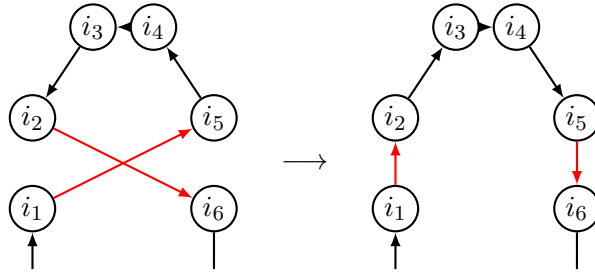


Figure 2: 2-Opt neighborhood.

5.2.4. Remove AFS

The move consists in removing an AFS from a route, if it improves the solution. Therefore, we iterate over all routes and check if it is possible to obtain a better solution removing the stop at the station. The procedure removes all the stops that can be skipped.

5.2.5. Relocate

The neighborhood relocates a customer. The final position can belong either to the same starting route or to another one. The procedure scans all the customers and checks if there exists at least another position to serve the customer that improves the solution. All the positions are examined, and the best one is selected.

5.3. Infeasibility management

The construction phase (Section 5.1) can lead to an infeasible solution. Indeed, Algorithm 2 does not check if the capacity constraints at AFSs are satisfied, and the scheduling of the refuels can yield routes exceeding T_{max} .

Therefore, the local search aims to either improve the cost of a feasible solution or restore its feasibility. This second purpose is accomplished through a penalty function $\phi(sol)$ that maps each solution in $[0, 1]$, where a feasible solution sol has $\phi(sol) = 0$. When comparing two solutions, all the local searches perform a lexicographic comparison on the pair penalty, routing cost. As a consequence, each feasible solution is better than all infeasible solutions.

Let $\hat{m}$ be the number of used AFVs (i.e., the number of routes of the solution), $\hat{T}$ the maximum duration of the routes, and $\hat{d}$ the maximum travelled distance by a vehicle without refueling or before and after a possible refueling, respectively. By defining $\bar{m} = \max\{\hat{m}, m\}$, $\bar{T} = \max\{T_{max}, \hat{T}\}$, and $\bar{d} = \max\{\hat{d}, D_{max}\}$, the penalty function ϕ is computed as

$$\phi(sol) = \frac{1}{3} \cdot \frac{\bar{m} - m}{\lceil 1.25m \rceil - m} + \frac{1}{3} \cdot \frac{\bar{T} - T_{max}}{1.5T_{max} - T_{max}} + \frac{1}{3} \cdot \frac{\bar{d} - D_{max}}{1.5D_{max} - D_{max}} \quad (3)$$

It is duly to note that all solutions where at least one among $\hat{m}$, $\hat{T}$ and $\hat{d}$ exceeds $\lceil 1.25m \rceil$, $1.5T_{max}$ and $1.5D_{max}$ respectively will be discarded.

6. Computational Results

6.1. Problem Instances and parameters setting

Four sets of instances are used for the computational study as detailed in the following. The first three sets have been introduced in Bruglieri et al. (2019b), whereas the last set is introduced for the first time in this paper to have a larger number of customers. In all the sets of instances, the average speed v is set equal to 40 miles per hour.

- **EMH Set:** 10 instances from the 40 proposed by Erdoğan & Miller-Hooks (2012) and considered challenging from the capacity point of view. They are in fact selected if in the optimal solution of G-VRP there are at least two AFVs visiting the same AFS. The original values of the parameters are kept, i.e., $T_{max} = 11$ hours, $p^{start} = 0.25$ hours, $p_s = 0.25$ hours $\forall s \in F$, $p_i = 0.5$ hours $\forall i \in I$, $Q = 60$ gallons and $r = 0.2$ gallons/mile (leading to $D_{max} = 300$ miles). The number of customers varies from 6 to 20, the number of AFSs from 3 to 10 and the number of AFVs from 3 to 8. As observed in Bruglieri et al. (2019b), since both the depot and AFSs are embedded in the customers area, refuels may happen at very different times along the routes or do not happen at all. For this reason, they can be considered slightly challenging for G-VRP-CAFS.
- **TRIANGLE Set:** 10 instances with 15 customers, 3 AFSs and 10 vehicles. The original parameters setting is kept, i.e., $T_{max} = 11$, $p^{start} = 0$, $p_s = 0.5$ $\forall s \in F$, $p_i = 0.75$ $\forall i \in I$, $Q = 50$ and $r = 0.2$ (leading to $D_{max} = 250$). As observed in Bruglieri et al. (2019b), a characteristic of these instances is that the stations lay in the middle between the depot and the customers. For this reason, each AFV needs to refuel, either at the beginning or at the end of its route leading to a more challenging scheduling problem. Therefore, these instances can be considered medium challenging.
- **CENTRAL set:** 10 instances with 15 customers, only one AFS, at the center of the customers area, and 15 vehicles. We keep the original parameters setting, i.e., $T_{max} = 7$, $p^{start} = 0$, $p_s = 0.5$ $\forall s \in F$, $p_i = 0.5$ $\forall i \in I$, $Q = 32$ and $r = 0.2$ (leading to $D_{max} = 160$). These instances have the depot far from the customers and the travel time from the depot to the station is 2 hours, leading to a very small time available for refuels. Since the station capacity may be a bottleneck, these instances are extremely challenging.
- **Large-sized CENTRAL set:** 10 instances with 25, 50 and 100 customers. All the parameters are set as in the CENTRAL set. Also the layout is similar to that used in the CENTRAL set, i.e., the depot is far from the customers area and the travel time from the depot to AFS is 2 hours. Moreover, the customers are clustered in clusters with at most 4 customers. These instances are generated with the following procedure. First of all, we compute the number $m = \lceil n/4 \rceil$ of vehicles sufficient to serve all the customers. We generate m random initial customers in a rectangle with height and base equal to 20 and 60, respectively, centered at the station. If n modulo 4 (i.e. the remainder of the division of n by 4) is 0, for each of the m initial customers we randomly generate 3 new customers so that they are not farther than

a certain threshold σ from the initial customer. Otherwise, for each of the first $m - 1$ initial customers, we randomly generate 3 new customers so that they are not farther than σ from the initial customer; for the $m - th$ initial customer we randomly generate $(n \bmod 4) - 1$ new customers so that they are not farther than σ from the $m - th$ customer. We choose $\sigma = 5$ to guarantee that the total distance travelled to serve the 4 customers associated with each route and visit the station is lower than 40 miles, i.e., can be covered within one hour (since the speed is of 40 miles/h). Indeed, this is the time that is left over considering $T_{max} = 7.5$ hours. In particular, 4 hours are necessary to reach the customer area from the depot and to go back to the depot, 2 hours are necessary to serve all the customers (being $p_i = 0.5 \forall i \in I$) and half an hour is necessary to refuel at AFS.

Moreover, the capacity η_s of each station s is set to 1, except in the large-sized instances where it is 2, 3 and 8 with 25, 50 and 100 customers, respectively. In what follows, we describe the tuning phase for the parameter related to the construction of the initial solutions in the GRASP framework, i.e., the parameter β of the Geometric Distribution that guides Biased Randomization and that belongs to the range $[0, 1]$.

To determine its best value, we consider a training set, by randomly selecting 30% of the instances EMH, TRIANGLE and CENTRAL. Then, we perform an *iterated racing procedure*, implemented in **irace** package López-Ibáñez et al. (2016), to automatically find the best configuration of β . On the basis of the experiments carried out by using the irace package, the best performance are obtained by setting $\beta = 0.23$. Thus, this setting is used in the testing phase.

6.2. Results on benchmark instances

In this section, on the first three sets of benchmark instances, we compare the results found by GRASP with those obtained by CP-Proactive, showed to reach the best performances in Bruglieri et al. (2019b).

The results are reported in Tables 2–4. The first column of each table reports the instance name, while the second and the third column indicate the *Total Distance* (TD) and the total *CPU Time* (in seconds) of CP-Proactive, respectively. The next two columns report the *Min Total Distance* (Min TD), i.e., the total distance obtained by the best solution found by GRASP and the *Avg Total Distance* (Avg TD), i.e., the average total distance on all the five runs performed by GRASP. Finally, the last two columns indicate the *Avg Time-to-best*, i.e., the average time within the GRASP method is suitable to find the best solution and the percentage *Gap* between the average total distance found by GRASP and the total distance of CP-Proactive, computed as follows:

$$GAP(\%) = \frac{(AvgTD - TD)}{TD} \cdot 100 \quad (4)$$

It is worth remarking that the total computational time given to GRASP on these instances is set equal to 1 minute.

Concerning the results comparison shown in Table 2, the *Avg TD* always equals *TD*; that means that all the solutions found by GRASP on each instance are optimal. Indeed, only on one instance (i.e., *S2_6i6s*), the *Avg TD* is slightly greater than *TD* (about 4.82%). However, the best solutions of GRASP are found in an average CPU time that is by far less than that of CP-Proactive (about 61.37%).

Moreover, the proposed approach closes to optimality all the Triangle instances in an average CPU time that is again by far less than that required by CP-Proactive (about 91.82%).

Finally, on the Central instances, our GRASP finds the same solution of the CP-Proactive approach in 60% of the cases, in an average CPU time that is by far less than that required by CP-Proactive (about 98.63%). Indeed, the only instance for which the solution of GRASP has a significant percentage gap is *Central4* that is also the case where CP-Proactive reaches the CPU time limit of 1 hour. This may be due to two factors. Firstly, the instances of this set are extremely challenging concerning the AFS capacity, as explained in their description. Secondly, *Central4* is the instance that has both the maximum average distance customer–depot, and the maximum average sum between distances customer–depot and customer–AFS.

Table 2: Results on EMH instances

Instance	CP-Proactive			GRASP		
	TD	CPU Time	Min TD	Avg TD	Avg Time-to-best	GAP(%)
20c3sC5	2156.01	1.45	2156.01	2156.01	0.23	0.00
20c3sC6	2758.17	0.3	2758.17	2758.17	0.22	0.00
20c3sC7	1393.99	0.49	1393.99	1393.99	0.02	0.00
20c3sC8	3139.72	0.65	3139.72	3139.72	0.88	0.00
20c3sC10	2583.42	6.82	2583.42	2583.42	0.10	0.00
20c3sU1	1797.49	13.42	1797.49	1797.49	0.75	0.00
S2_2i6s	1633.10	65.58	1633.10	1633.10	3.46	0.00
S2_6i6s	2431.33	2.31	2431.33	2548.50	29.61	4.82
S2_8i6s	2158.35	0.81	2158.35	2158.35	0.18	0.00
S2_10i6s	1585.46	1.95	1585.46	1585.46	0.53	0.00
Average	2227.95	10.20	2227.95	2240.97	3.94	0.58

6.3. Results on large-sized instances

Regarding the large-sized instances proposed in this work, it was prohibitive to solve them with the path-based approaches proposed in Bruglieri

Table 3: Results on Triangle instances

Instance	CP-Proactive		GRASP			
	TD	CPU Time	Min TD	Avg TD	Avg Time-to-best	GAP(%)
Triangle1	1871.61	1.04	1871.61	1871.61	1.63	0.00
Triangle2	2191.73	4.09	2191.73	2191.73	0.52	0.00
Triangle3	1872.12	4.56	1872.12	1872.12	0.59	0.00
Triangle4	1869.07	4.52	1869.07	1869.07	0.05	0.00
Triangle5	1852.73	11.02	1852.73	1852.73	0.19	0.00
Triangle6	1865.49	5.25	1865.49	1865.49	0.33	0.00
Triangle7	1898.00	3.10	1898.00	1898.00	1.11	0.00
Triangle8	2197.49	13.76	2197.49	2197.49	0.20	0.00
Triangle9	1862.50	6.30	1862.50	1862.50	0.07	0.00
Triangle10	1864.73	5.04	1864.73	1864.73	0.07	0.00
Average	1934.55	5.87	1934.55	1934.55	0.48	0.00

Table 4: Results on Central instances

Instance	CP-Proactive		GRASP			
	TD	CPU Time	Min TD	Avg TD	Avg Time-to-best	GAP(%)
Central1	953.94	130.61	953.94	953.94	44.72	0.00
Central2	948.69	441.91	959.88	959.88	10.19	1.18
Central3	943.12	3600.00	958.94	959.37	15.78	1.72
Central4	967.96	3600.00	1099.24	1110.27	23.59	14.70
Central5	714.55	2.98	714.55	714.55	0.05	0.00
Central6	844.43	1348.23	844.43	844.43	0.17	0.00
Central7	862.68	148.07	862.68	862.68	22.11	0.00
Central8	712.83	4.60	712.83	712.83	0.33	0.00
Central9	855.43	22.10	855.43	855.43	0.11	0.00
Central10	901.19	453.02	905.59	906.29	16.23	0.57
Average	870.48	975.15	886.75	887.97	13.33	2.01

et al. (2019b). Indeed, on the instances with 25 customers, almost 300 thousands *pairs* are generated on average; on the instances with 50 customers, more than 2 millions; on the instances with 100 customers, even the phase of generating all the feasible non-dominated paths failed since the CPU time limit of 1 hour was exceeded. As a consequence, only the results obtained by GRASP in 2 minutes of running time are presented and discussed.

Each of the next three tables (Tables 5–7) reports, for each instance, the Minimum Travel Distance (*MinTD*), the Average Total Distance (*AvgTD*), the Average Time-to-best (in seconds) and finally, the average number of AFVs used and refuelings required.

On the instances with 25 customers, the solutions found by GRASP differ from the best ones by about 0.19%, on average. The average number of EVs used is equal to 6.30, each of them refueling once except in one case (instance Central25_9 where there is one EV not refueling).

On the instances with 50 customers, the solutions found are far from the best ones on average by about 0.87% using 12.94 EVs, each of them refueling at most once.

Finally, on the instances with 100 customers, the solutions found are far from the best ones on average by about 0.53% using about 25 EVs, each of them refueling almost always once.

Table 5: Results on Central instances with 25 customers

Instance	GRASP				
	Min TD	Avg TD	Avg Time-to-best	AFVs used	Refuelings
Central25.1	1129.85	1135.88	73.56	6.00	6.00
Central25.2	1113.97	1115.14	70.92	6.00	6.00
Central25.3	1321.82	1323.10	62.62	7.00	7.00
Central25.4	1122.73	1123.73	80.97	6.00	6.00
Central25.5	1110.36	1116.28	87.55	6.00	6.00
Central25.6	1090.04	1090.39	44.18	6.00	6.00
Central25.7	1105.04	1106.89	37.15	6.00	6.00
Central25.8	1141.23	1144.17	47.77	6.00	6.00
Central25.9	1281.57	1281.98	42.65	7.00	6.80
Central25.10	1311.67	1313.26	82.07	7.00	7.00
Average	1172.83	1175.08	62.94	6.30	6.28

On all the tested instances we verify the effectiveness of the different moves considering the average percentage improvement provided by each kind of move. The most effective move is the *Destroy route* with an average improvement of 3.74%. The second most effective move is the *Relocate* move with an average improvement of 0.30%, followed by the 2 – *Opt* and *RemoveAFS* moves with an average improvement of 0.25% and 0.11%, respectively.

Table 6: Results on Central instances with 50 customers

Instance	GRASP				
	Min TD	Avg TD	Avg Time-to-best	AFVs used	Refuelings
Central50_1	2520.33	2533.43	78.06	13.00	13.00
Central50_2	2435.78	2448.75	71.69	13.00	12.80
Central50_3	2425.64	2447.54	58.90	13.00	13.00
Central50_4	2271.14	2330.86	71.00	12.40	12.00
Central50_5	2467.29	2482.22	61.25	13.00	13.00
Central50_6	2422.87	2457.04	62.84	13.00	12.60
Central50_7	2405.19	2435.18	73.27	13.00	12.00
Central50_8	2487.32	2487.32	44.37	13.00	13.00
Central50_9	2450.04	2458.80	49.76	13.00	13.00
Central50_10	2473.63	2489.88	73.41	13.00	13.00
Average	2435.92	2457.10	64.46	12.94	12.74

Table 7: Results on Central instances with 100 customers

Instance	GRASP				
	Min TD	Avg TD	Avg Time-to-best	AFVs used	Refuelings
Central100_1	4966.03	5000.79	82.23	25.00	25.00
Central100_2	4730.11	4746.06	90.05	25.00	24.67
Central100_3	4757.50	4782.34	87.17	25.00	25.00
Central100_4	4697.35	4726.88	80.93	25.00	25.00
Central100_5	4732.49	4753.31	120.93	25.00	25.00
Central100_6	4524.44	4603.63	91.32	24.40	24.40
Central100_7	4786.57	4790.82	57.06	25.00	25.00
Central100_8	4784.18	4808.73	40.25	25.00	25.00
Central100_9	4795.70	4795.70	66.51	25.00	25.00
Central100_10	4686.57	4705.79	63.06	25.00	25.00
Average	4746.09	4771.40	77.95	24.94	24.90

6.3.1. Sensitivity analysis of move performances

In this Section, a sensitivity analysis of the move performances is presented on the large-sized instances.

Table 8: Move performances

$ I $	Destroy Route		2-Opt		Relocate		Remove AFS		Change Station	
	SF	SQ	SF	SQ	SF	SQ	SF	SQ	SF	SQ
25	8.72	14.07	0.00	1.38	0.00	1.58	0.00	0.70	0.22	0.00
50	0.46	7.93	0.00	0.11	0.00	0.17	0.00	0.02	0.00	0.00
100	1.03	4.02	0.00	0.04	0.00	0.08	0.00	0.00	0.94	0.00
Average	3.48	8.82	0.00	0.53	0.00	0.63	0.00	0.25	0.37	0.00

Table 8 reports the performances of the moves *Destroy Route*, *2-Opt*, *Relocate*, *Remove AFS* and *Change Station*. On the one hand, the column *SF* shows the average percentage of times in which each of them restores the solution feasibility. On the other hand, the column *SQ* shows the average percentage improvement computed as follows

$$SQ = \frac{(c - fc)}{c} \cdot 100 \quad (5)$$

where c and fc denote the cost of the feasible solution before and after the local search, respectively. As expected, on average, the move *Destroy Route* performs the best on both restoring the solution feasibility and improving the solution quality. Whereas, the move *Change Station* performs the worst on improving the solution quality; the moves *2-Opt*, *Relocate* and *Remove AFS* perform the worst on restoring the solution feasibility.

Finally, on average, the percentage of times in which an overlapping at the station is observed is 91.31, 98.44 and 99.42 in the instances with 25, 50 and 100 customers, respectively. As expected, the average percentage increases by increasing the number of AFVs used (Tables (5)-(7)). Readers are referred to the Appendix for the details on the sensitivity analysis.

6.3.2. The effect of changing station capacity on the number of vehicles used

The aim of this section is to show how changing the AFS capacity may affect the number of AFVs used on the large-sized instances with 100 customers. We have increased by one the AFS capacity from 8 to 16, being the latter the maximum value for which we have observed a decrease in the number of AFVs used (Figure 3). Figure 4 shows how the number of the large-sized instances solved by GRASP considering a fleet of 24 AFVs increases as AFS capacity increases too. In particular, with 16 pumps, GRASP solved all the large-sized instances with 24 AFVs.

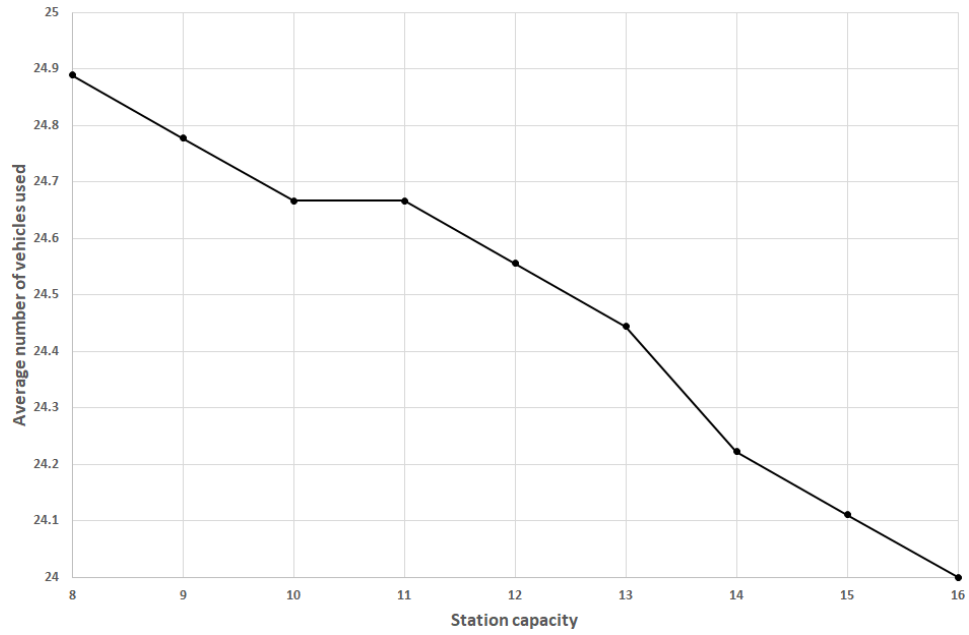


Figure 3: Average number of AFVs used versus AFS capacity.

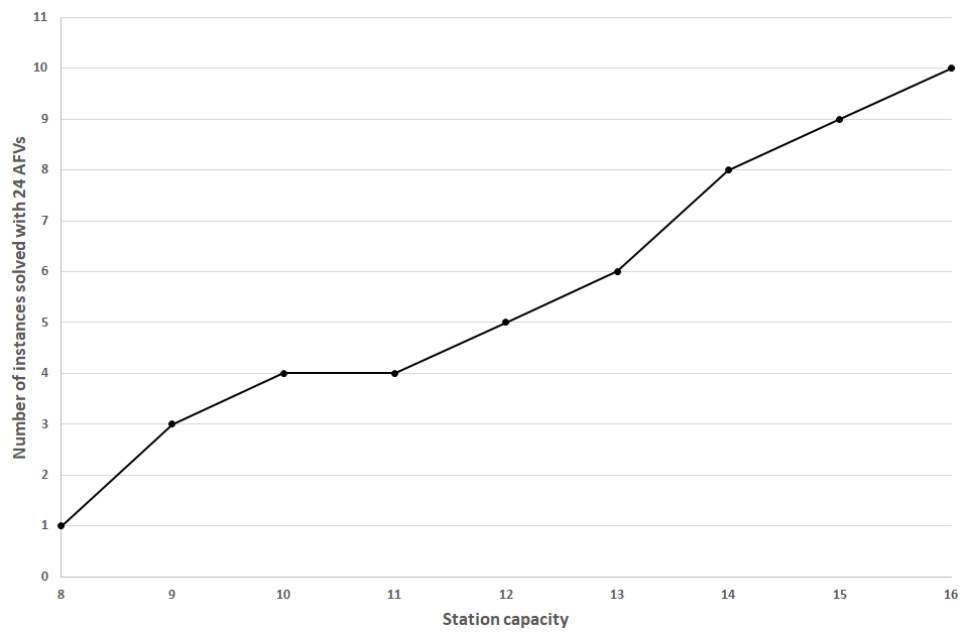


Figure 4: Number of instances solved with 24 AFVs versus AFS capacity.

7. Conclusions and Future Work

In this paper, we proposed a Greedy Randomized Adaptive Search Procedure (GRASP) for the Green Vehicle Routing Problem with Capacitated Alternative Fuel Stations (G-VRP-CAFS). G-VRP-CAFS aims at routing a fleet of Alternative Fuel Vehicles (AFVs), each one starting and ending in a common depot, serving a set of customers at the minimum total distance, within a maximum duration. Along the routes, each AFV is allowed to refuel at the Alternative Fuel Stations (AFSs) supposed to have a limited number of fueling pumps. This implies that only a certain number of AFVs can simultaneously refuel at the same station. G-VRP-CAFS was introduced in Bruglieri et al. (2019b) and solved through an exact approach on a set of benchmark instances with up to 20 customers.

The aim of this work was to design a metaheuristic based on the GRASP framework in order to efficiently address also large-sized instances of G-VRP-CAFS with even 100 customers. Some theoretical results on the compatibility among routes were also detected in order to properly guide GRASP. Moreover, along the local search, possible violations on the route duration were allowed and properly faced through a penalty objective function in order to better explore the neighborhoods.

Computational results were carried out on both the sets of benchmark instances taken from Bruglieri et al. (2019b) and a set of large-sized instances specifically introduced in this paper. In particular, the results obtained by GRASP on the benchmark instances were compared with those found by the CP-Proactive approach proposed in Bruglieri et al. (2019b) and shown to reach the best performances. The proposed GRASP was suitable to close to optimality about 83% of the instances with an average time-to-best (the time required by GRASP to obtain the best solution among those generated) that is by far less (about 98%) than the total computational time required by CP-Proactive. Finally, GRASP was shown to efficiently address also the large-sized instances in an average time-to-best equal to about 1 minute.

Future works may concern the design and comparison of other Destroy route operators, the introduction of time windows at customers as well as the extension of the proposed procedure to similar problems, such as, the VRP with Intermediate Facilities and the Electric VRP where, unlike G-VRP, the refueling time is not constant but depends on the vehicle state of charge. In addition, G-VRP can be also addressed with heterogeneous AFSs, i.e., stations with different capacity. Finally, since fuel consumption plays a key role in G-VRP-CAFS, a possible extension may also take into account vehicle load and speed, ambient temperature and road gradient as factors affecting the refuel need.

Appendix. Detailed Sensitivity analysis of the move performances

The following tables report the detailed sensitivity analysis of the move

performances on each sub-set of large-sized instances (i.e., with 25, 50 and 100 customers).

Table 9: Move performances on the instances with 25 customers

	Destroy Route		2-Opt		Relocate		Remove AFS		Change Station		
Instance	SF	SQ	SF	SQ	SF	SQ	SF	SQ	SF	SQ	OL
Central25_1	8.20	13.55	0.01	1.51	0.00	1.68	0.00	0.78	0.09	0.00	91.29
Central25_2	9.86	14.33	0.00	1.32	0.00	1.81	0.00	0.37	0.17	0.00	91.86
Central25_3	3.44	14.74	0.00	0.77	0.00	0.66	0.00	0.00	0.00	0.00	95.41
Central25_4	8.43	13.89	0.00	1.12	0.00	1.70	0.00	1.76	0.13	0.00	88.79
Central25_5	10.42	14.00	0.00	1.79	0.00	1.62	0.00	0.69	0.41	0.00	90.93
Central25_6	13.62	14.41	0.01	2.08	0.00	2.67	0.00	0.62	0.62	0.00	88.57
Central25_7	9.95	14.46	0.01	1.76	0.00	1.86	0.00	0.82	0.62	0.00	88.49
Central25_8	8.50	13.48	0.00	1.62	0.00	1.47	0.00	1.58	0.09	0.00	92.07
Central25_9	9.21	13.88	0.00	1.20	0.00	1.51	0.00	0.33	0.03	0.00	92.35
Central25_10	5.53	13.99	0.00	0.67	0.00	0.84	0.00	0.08	0.02	0.00	93.37
Average	8.72	14.07	0.00	1.38	0.00	1.58	0.00	0.70	0.22	0.00	91.31

Table 10: Move performances on the instances with 50 customers

	Destroy Route		2-Opt		Relocate		Remove AFS		Change Station		
Instance	SF	SQ	SF	SQ	SF	SQ	SF	SQ	SF	SQ	OL
Central50_1	0.03	8.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.33
Central50_2	0.72	7.90	0.00	0.16	0.00	0.32	0.00	0.00	0.00	0.00	98.86
Central50_3	0.49	7.71	0.00	0.12	0.00	0.37	0.00	0.00	0.01	0.00	98.03
Central50_4	1.54	7.48	0.00	0.12	0.00	0.36	0.00	0.00	0.02	0.00	97.83
Central50_5	0.15	8.06	0.00	0.11	0.00	0.05	0.00	0.00	0.00	0.00	98.52
Central50_6	0.37	8.18	0.00	0.12	0.00	0.09	0.00	0.00	0.00	0.00	98.32
Central50_7	0.36	7.42	0.00	0.11	0.00	0.23	0.00	0.24	0.01	0.00	97.77
Central50_8	0.07	8.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	98.76
Central50_9	0.74	7.97	0.00	0.20	0.00	0.18	0.00	0.00	0.00	0.00	98.70
Central50_10	0.19	8.09	0.00	0.10	0.00	0.08	0.00	0.00	0.00	0.00	98.29
Average	0.46	7.93	0.00	0.11	0.00	0.17	0.00	0.02	0.00	0.00	98.44

Tables (9)-(11) show the average percentage of times in which the moves *Destroy Route*, *2-Opt*, *Relocate*, *Remove AFS* and *Change Station* restore the solution feasibility (column SF) and improve the solution quality of already feasible solutions (column SQ), on the instances with 25, 50 and 100 customers, respectively. The values of SQ are computed through formula (5). Moreover, the column OL reports the average percentages in which an overlapping at the station is detected, on the instances with 25, 50 and 100 customers, respectively.

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Table 11: Move performances on the instances with 100 customers

	Destroy Route		2-Opt		Relocate		Remove AFS		Change Station		
Instance	SF	SQ	SF	SQ	SF	SQ	SF	SQ	SF	SQ	OL
Central100_1	2.64	3.36	0.00	0.07	0.00	0.22	0.00	0.05	9.41	0.00	99.75
Central100_2	0.46	4.23	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	99.63
Central100_3	0.68	4.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.19
Central100_4	1.19	4.19	0.00	0.04	0.00	0.18	0.00	0.00	0.00	0.00	99.08
Central100_5	0.50	4.19	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	99.47
Central100_6	1.85	3.88	0.00	0.06	0.00	0.20	0.00	0.00	0.00	0.00	99.40
Central100_7	0.60	3.89	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	99.45
Central100_8	0.42	4.04	0.00	0.05	0.00	0.08	0.00	0.00	0.00	0.00	99.31
Central100_9	0.29	4.03	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	99.76
Central100_10	1.71	4.12	0.00	0.12	0.00	0.06	0.00	0.00	0.00	0.00	99.16
Average	1.03	4.02	0.00	0.04	0.00	0.08	0.00	0.00	0.94	0.00	99.42

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