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Routing a hybrid fleet of conventional and electric vehicles: the case of a French utility

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1 Introduction

Motivated by stricter environmental regulations, government incentives, branding opportunities, and potential reductions in operational costs, companies all around the world are renewing their fleets with electric vehicles (EVs). One of the main challenges faced by companies in the transition to *clean fleets* is the lack of fleet management tools that are able to handle hybrid fleets of "conventional" and electric vehicles (hereafter CVs and EVs). In this talk we present a study carried in collaboration with French electricity giant EDF to try to address this challenge. More precisely, we describe the technician routing and scheduling problem with CVs and EVs (TRSP-CEV) faced by ENEDIS (an EDF subsidiary) and present a decomposition-based parallel matheuristic to solve it. We show results on real data provided by the company and discuss managerial insight into the impact of the fleet composition (percentage of EVs vs. CVs) in the feasibility and cost of the solutions.

2 Problem description

The TRSP-CEV can be defined on a directed and complete graph $G = (\mathcal{N}, \mathcal{A})$ where $\mathcal{N}$ is the set of nodes and $\mathcal{A}$ is the set of arcs. The set of nodes is defined as $\mathcal{N} = \{0\} \cup \mathcal{C} \cup \mathcal{S}$, where node 0 represents the depot, $\mathcal{C}$ is a set of nodes representing the customers, and $\mathcal{S}$ is a set of nodes representing the charging stations (CSs) where the electric vehicles can recharge their batteries. Each customer $i \in \mathcal{C}$ has a request demanding a skill k_i from a set $\mathcal{K}$ and having a service time p_i and a time window $[ec_i, lc_i]$, where ec_i and lc_i are the earliest and latest possible service start times. For simplicity, hereafter we use the terms customer and request interchangeably. Each CS $c \in \mathcal{C}$ has a *parking cost* (in €/min) representing the cost of the charging time at that station. The set of technicians is denoted as $\mathcal{T}$. Each technician $t \in \mathcal{T}$ has: a fixed daily cost c_t; a subset of skills $\mathcal{K}_t \subseteq \mathcal{K}$; a shift $[es_t, ls_t]$, where es_t is the technician's earliest possible departure time from the depot and ls_t is the technician's latest return time to the depot; a lunch break that must start at el_t and end at ll_t; and an *energy consumption factor* cf_t associated to the technician's driving profile (e.g., sportive, normal, eco). To cover their routes, the technicians drive vehicles belonging to a fixed fleet composed by different types of CVs and EVs. The set of vehicle types is defined as $\mathcal{V} = \mathcal{V}_c \cup \mathcal{V}_e$, where $\mathcal{V}_c$ is the set of CV types and $\mathcal{V}_e$ is the set of EV types. For each vehicle type $v \in \mathcal{V}$ there is a travel cost tc_v (in €$/km$) and a fixed and limited number of vehicles m_v. Vehicles of type $v \in \mathcal{V}_e$ additionally have: a fixed cost gc_v for recharging the battery (in €)[1], a battery capacity Q_v (in kWh), a set $\mathcal{S}_v \subseteq \mathcal{S}$ of compatible CSs, and a discrete and non-linear charging function f_{vs} describing the relation between the vehicle's charging time and *state of charge* (SoC) at station $s \in \mathcal{S}_v$. Depending on the context we refer to the SoC as the amount of remaining energy (in kWh) or as the percentage of remaining battery capacity. The charging function is defined as $f_{vs} = \{a_b | b \in \{0, 1, \ldots, 100\}\}$ were a_b is the time needed to take the SoC from 0 to b percent of Q. Finally, set $\mathcal{A} = \{(i, j) : i, j \in \mathcal{N}, i \neq j\}$ denotes the set of arcs connecting nodes in $\mathcal{N}$. Each arc $(i, j) \in \mathcal{A}$ has three associated nonnegative values: a travel time tt_{ij}, a distance d_{ij}, and a nominal energy consumption e_{ijv} for each type of EV $v \in \mathcal{V}_e$.

In the TRSP-CEV the objective is to find a set of routes of minimum total cost. The latter is defined as the sum of i) travel costs, ii) fixed charging costs, iii) parking costs, and iv) technician utilization costs. The planned set of routes must satisfy the following constraints: each request is served exactly once within its time window by a technician with the required skill; the level of the battery when the EVs arrive at any vertex is nonnegative; the EVs only charge at compatible CSs; each technician works only during his or her shift; each technician takes the lunch break at the pre-defined times; the number of vehicles of type $v \in \mathcal{V}$ used in the plan is less or equal than m_v; and each route starts and ends at the depot.

[1] This cost accounts for the long-term battery degradation cost

Algorithm 1 Parallel matheuristic: general structure

1: **function** ParallelMatheuristic(G,$\mathcal{T}$,$\mathcal{V}$)
2: $\mathcal{TP} \longleftarrow$ `groupTechnicians(`$\mathcal{T}$`)`
3: $\mathcal{TV} \longleftarrow$ `buildAssignments(`$\mathcal{TP}$`,`$\mathcal{V}$`)`
4: $\Omega \longleftarrow \emptyset$
5: **parallel for each** $tv \in \mathcal{TV}$
6: $\Omega_{tv} \longleftarrow$ `GRASP(`tv`,`G`)`
7: $\Omega \longleftarrow \Omega \cup \Omega_{tv}$
8: **end for**
9: $\sigma \longleftarrow$ `setCovering(`G`,`Ω`,`$\mathcal{V}$`,`$\mathcal{TV}$`)`
10: **return** σ
11: **end function**

3 Parallel matheuristic

Algorithm 1 describes the general structure of our parallel matheuristic (here after referred to as PMa). The algorithm starts by calling procedure `groupTechnicians(`$\mathcal{T}$`)` – line 2. This procedure groups the technicians sharing the same characteristics (i.e., skills, fixed utilization cost, energy consumption factor, shift, and lunch break) and generates the set $\mathcal{TP}$ of *technician profiles*. Then, the algorithm invokes procedure `buildAssignments(`$\mathcal{TP}, \mathcal{V}$`)` – line 3. The latter builds the set $\mathcal{TV}$ containing all possible technician profile-vehicle type assignments. Note that $|\mathcal{TV}| = |\mathcal{TP}| \times |\mathcal{V}_c| + |\mathcal{TP}| \times |\mathcal{V}_e|$. Then, the algorithm starts the parallel phase – lines 5 to 8. For each assignment $tv \in \mathcal{TV}$ the algorithm solves, on a dedicated thread, a vehicle routing problem with time windows and lunch breaks (VRP-TWLB). Let $p(tv) \in \mathcal{TP}$ and $v(tv) \in \mathcal{V}$ be the technician profile and the type of vehicle involved in assignment tv. In the VRP-TWLB for assignment tv we assume that i) the fleet is unlimited and composed only of vehicles of type $v(tv)$ and that we have an unlimited number of technicians with profile $p(tv)$. If $v(tv)$ is an EV, then the resulting problem is an electric VRP-TWLB. To solve the $|\mathcal{TP}| \times |\mathcal{V}_c|$ VRPs-TWLB and the $|\mathcal{TP}| \times |\mathcal{V}_e|$ eVRPs-TWLB our approach relies on a GRASP (line 6). The GRASP slightly varies depending on the type of problem being solved (VRP-TWLB or eVRP-TWLB). Figure 1 depicts the components embedded in the two versions. The GRASP returns a set Ω_{tv} containing all the routes found in the local optima reached during the algorithm's execution. The routes in $\Omega_t v$ join the *long term memory* structure Ω (line 7). After completing the parallel phase, the algorithm calls procedure `setCovering(`G`,`Ω`,`$\mathcal{V}$`,`$\mathcal{TV}$`)` – line 9 –, which solves an extended set covering formulation over Ω to find a feasible TRSP-CEV solution. It is worth noting that it is only at this point that we take into account the constraints on the number of technicians and vehicles. Full details on the GRASP components, specially those used to solve the eVRPs-TWLB, and the parallel implementation will be discussed in the talk.

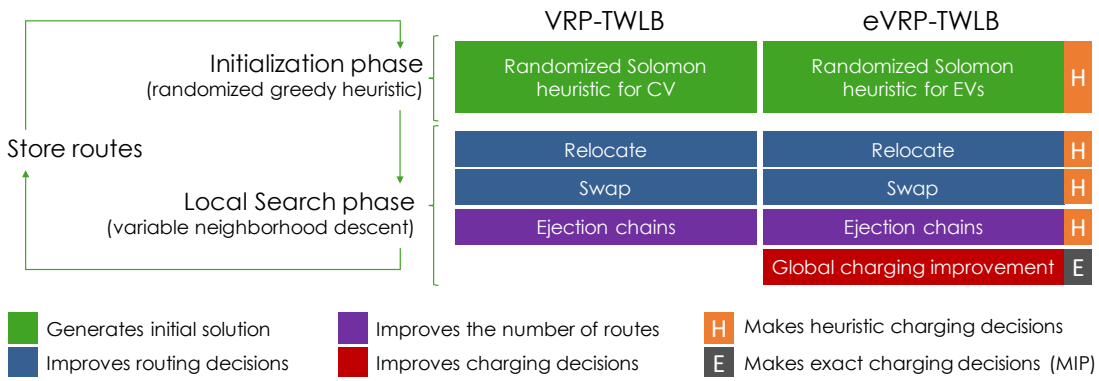

Figure 1: Algorithmic components embedded in the two GRASP versions

4 Computational experiments

We ran experiments on two sets of instances. The first set is made up of 24 "real-world" TRSP instances (10 small with proven optima + 14 large) built using data provided by ENEDIS. For the 10 small instances our PMa was able to find the optimal solutions. For the remaining 14 instances PMa reported average improvements of 6.5% with respect to the solutions delivered by the software currently used at ENEDIS. We adapted the instances to the TRSP-CEV by setting the portion of EVs in the fleet to $\{20\%, 40\%, 60\%, 80\%, 100\%\}$. We ran experiments to evaluate the impact of the fleet composition on the total cost and feasibility of the solutions. We found that for urban settings, transitioning to a 100% electric fleet is feasible and may generate considerable savings in cost and emissions. On the other hand, to obtain feasible solutions for all rural instances, only 20% of the fleet can be replaced by EVs. The second instance set consists of the 276 instances (108 small with proven optima + 168 large) proposed in [1] for the closely-related electric fleet size and mix vehicle routing problem with time windows and recharging stations. Although our method was not tailored for this problem, it was able to deliver competitive perfomances with respect to the state-of-the-art Adaptive Large Neighborhood Search (ALNS) proposed in [1]. On the small instances our PMa found 81/108 optimal solutions and reported better avg. gaps (0.32% vs 0.55%) and execution times (0.06min vs. 0.32min) than ALNS. On the large instances, our method unveiled 61 new best known solutions but reported larger avg. gaps than ALNS (2.20% vs. 1.18%) with comparable execution times.

References

[1] G. Hiermann, J. Puchinger, S. Ropke, and R. F. Hartl. The electric fleet size and mix vehicle routing problem with time windows and recharging stations. *European Journal of Operational Research*, 252(3):995–1018, 2016.