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Juan Villegas, Christelle Guéret, Jorge E. Mendoza, Alejandro Montoya

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Juan G. Villegas[1] Christelle Guéret[2] Jorge E. Mendoza[3]
Alejandro Montoya[4]

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[1] Departamento de Ingeniería Industrial, Facultad de Ingeniería, Universidad de Antioquia
Calle 70 No. 52-21, 050010 Medellín, Colombia

[2] Université d'Angers, LARIS (EA 7315)
62 avenue Notre Dame du Lac, 49000 Angers, France

[3] Université de Tours, LIFAT (EA 6300), ROOT (ERL CNRS 7002)
64 avenue Jean Portalis, 37200 Tours, France

[4] Departamento de Ingeniería de Producción, Universidad EAFIT
Carrera 49 No. 7 Sur - 50, Medellín, Colombia

Abstract

Motivated by stricter environmental regulations, government incentives, branding opportunities, and potential cost reductions, companies are replacing their conventional vehicles (CVs) with electric vehicles (EVs). However, due to financial and operational restrictions, these fleet transitions usually occur in several stages. This introduces new operational challenges, because most existing fleet management and routing tools are not designed to handle hybrid fleets of CVs and EVs. In this paper, we study a problem arising in the daily operations of telecommunication companies, public utilities, home healthcare providers, and other businesses: the technician routing and scheduling problem with conventional and electric vehicles (TRSP-CEV). To solve this problem we propose a two-phase parallel matheuristic. In the first phase the matheuristic decomposes the problem into several vehicle routing problems with time windows, and it solves these problems (in parallel) using a greedy randomized adaptive search procedure (GRASP). At the end of each GRASP iteration, the routes making up the local optimum are stored in long-term memory. In the second phase, the method uses the stored routes to find a TRSP-CEV solution. We discuss computational experiments on industrial instances provided by a French utility. We provide managerial insight into the impact of the proportion of EVs in the fleet on metrics such as the number of routes, the total operational cost, and the CO_2 emissions. Additionally, we present state-of-the-art results for the closely related electric fleet size and mix vehicle routing problem with time windows and recharging stations.

1 Introduction

Electric vehicles (EVs) include hybrids, plug-in hybrids, and battery electric vehicles. Although their market share is still small, it is increasing thanks to government incentives and technological improvements. The benefits of EVs include reductions in noise and local greenhouse gas emissions, their lower operational cost with respect to conventional vehicles (CVs), their contribution to a green corporate image, and their suitability for low-emission zones. However, the large-scale adoption of EVs is still hampered by economical and technical constraints such as the high upfront cost, low driving range, and long battery charging time, as well as the limited availability of charging infrastructure (Pelletier et al., 2014). Commercial EVs are mostly used in urban operations such as last-mile distribution (Taefi et al., 2015) and technical and home care services (ENEDIS, 2015; Yavuz et al., 2015). Indeed, service vehicles form the first market segment where EVs are expected to match CVs in terms of total cost of ownership (Electrification Coalition, 2010).

EVs are evolving rapidly, so there is uncertainty about their future operational capacities and costs (e.g., maintenance cost, energy price, battery lifetime, charging time). For this reason, the transition to cleaner fleets usually occurs in several stages (Kleindorfer et al., 2012; Sierzchula, 2014). During the transition, companies operate hybrid fleets with both EVs and CVs. This introduces new operational challenges, because most existing fleet management and routing tools are not designed to handle hybrid

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fleets. To contribute to the toolbox available to companies operating in this context, we introduce the technician routing and scheduling problem with conventional and electric vehicles (TRSP-CEV). The TRSP-CEV designs routes that take into account the customers' time windows (TWs) and the drivers' skills, shifts, and lunch breaks. In the TRSP-CEV there is a fixed and heterogeneous fleet of CVs and EVs. Due to their relatively limited driving ranges, EVs may need to include one or more recharging stops in their routes. To solve the problem, we propose a parallel matheuristic. The approach has two phases. In the first phase we decompose the problem into a number of simpler vehicle routing problems (VRPs) with TWs and solve these problems in parallel using a greedy randomized adaptive search procedure (GRASP). The routes making up the local optima are stored in long-term memory. In the second phase, we solve a set covering problem over the stored routes to find a solution for the TRSP-CEV.

The main contributions of this paper are fourfold. First, we introduce a complex new VRP, namely the TRSP-CEV. Second, we propose a decomposition scheme that can be extended to other VRP variants. Third, we propose a set of test instances based on (i) the operation of a public utility, (ii) real charging infrastructure availability, and (iii) realistic energy consumption and charging functions. Fourth, we analyze the solutions of TRSP-CEV instances with different geographical characteristics and fleet compositions to provide insights into the impact of the introduction of EVs in field maintenance operations. Additionally, we report state-of-the-art solutions for the closely related electric fleet size and mix VRP with TWs and recharging stations (E-FSMVRPTW).

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 formally defines the TRSP-CEV and presents a mixed integer linear programming (MILP) formulation. Section 4 introduces our parallel matheuristic. Section 5 presents the computational experiments and reports the results from our parallel matheuristic on the Hiermann et al. (2016) instances for the E-FSMVRPTW. Section 6 provides concluding remarks.

2 Literature review

The TRSP-CEV integrates the elements of two (complex) (VRPs): the VRP with CVs and EVs (Goeke & Schneider, 2015) and the workforce scheduling and routing problem (Castillo-Salazar et al., 2016). We now briefly survey the most relevant literature on these two problems. See Pelletier et al. (2016) for a recent review of electric VRPs and Castillo-Salazar et al. (2016) and Paraskevopoulos et al. (2017) for reviews of workforce scheduling and routing problems.

2.1 Electric vehicle routing problems

The main feature of electric VRPs (E-VRPs) is that they explicitly model the limited range of EVs. In consequence, they deal not only with classical routing decisions (e.g., customer sequencing) but also with charging decisions (where and how much energy to charge). Early work on E-VRPs makes simplifying assumptions about the charging operations. For instance, Conrad & Figliozzi (2011) studied an E-VRP where the charging stations (CSs) are located at the customer locations (i.e., no detours are needed). Likewise, in the green VRP, Erdoğan & Miller-Hooks (2012) assume that fully recharging the battery takes a constant time. More recently, authors have started to relax these assumptions. Felipe et al. (2014) studied an E-VRP where the stations have multiple charging technologies (i.e., speeds). They also allow partial charging, i.e., the amount of energy charged is a decision variable. They use a multi-neighborhood local search heuristic and simulated annealing. Schneider et al. (2014) introduced the E-VRP with TWs and recharging stations (E-VRPTW) in which the customers must be served within a specified time interval (i.e., the TW). They assume that the charging time is variable and depends on the state of charge (SoC) on arrival at the CS; they do not allow partial charging. They propose a hybrid metaheuristic combining tabu search and variable neighborhood search (VNS). Later, Schneider et al. (2015) improved their results by combining their VNS with an adaptive large neighborhood search (ALNS). Keskin & Čatay (2016) extended the E-VRPTW to partial recharging and proposed an ALNS. Desaulniers et al. (2016) developed a branch-and-price-and-cut algorithm for E-VRPTW variants with full or partial recharging. Their method consistently solves instances with up to 100 customers and 21 charging stations. In the TRP-CEV, we consider CSs with different technologies, allow partial recharging, and model the charging time as a decision variable.

As pointed out by Pelletier et al. (2017), modeling the behavior of the battery (during charging, storage, and discharging) is a challenging task. In most studies, the charging function is assumed to be linear with respect to the charging time (Schneider et al., 2014; Felipe et al., 2014; Schneider et al., 2015; Keskin & Čatay, 2016; Desaulniers et al., 2016). In practice, however, the SoC is a logarithmic function of the charging time. To deal with this, Montoya et al. (2017) studied the E-VRP with a nonlinear charging function (E-VRP-NL); a problem in which the charging function is approximated using a piecewise linear expression. They show that approximating the charging function using linear expressions may lead to solutions that are either infeasible or overly expensive. They propose a matheuristic based on iterated local search (ILS) and a set partitioning post-optimizer to solve E-VRP-NL instances with up to 320 customers. More recently, Froger et al. (2017) have introduced enhanced mixed integer programming formulations for the E-VRP-NL.

The energy consumption of EVs is another factor that has been simplified in the literature. Most E-VRP models assume that the energy consumption is a linear function of the traveled distance (Erdoğan & Miller-Hooks, 2012; Schneider et al., 2014; Felipe et al., 2014; Schneider et al., 2015; Keskin & Čatay, 2016). However, Goeke & Schneider (2015) use speed, road gradient, and cargo load to estimate the energy consumption of both EVs and CVs. Similarly, Murakami (2017) describes an energy consumption model that takes into account road gradient, vehicle speed and acceleration, and waiting time at traffic lights. In the TRSP-CEV, we model the charging functions using nonlinear expressions, and we use realistic energy consumption estimates based on real road network parameters and EV characteristics.

Only a few researchers have considered hybrid fleets of CVs and EVs, and to the best of our knowledge Juan et al. (2014) were the first to do so. They introduced the VRP with multiple driving ranges (VRPMDR) in which they consider a hybrid fleet of CVs, EVs, and plug-in hybrid EVs (PHVs). They do not consider en-route recharging. Therefore, their problem can be seen as a classical VRP with a heterogeneous fleet in which each vehicle type has a different range. They propose a multi-round heuristic that solves several homogeneous-fleet VRPs sequentially. Each VRP in the sequence has a maximum-distance constraint that depends on the vehicle used. Goeke & Schneider (2015) studied the routing of hybrid fleets with en-route recharging. They introduced the VRP with conventional and electric vehicles (VRP-CEV) and proposed an ALNS. Computational experiments showed that minimizing the traveled distance (ignoring the fuel, labor, and battery degradation costs) leads to solutions that are 5% more expensive than those obtained if these terms are included in the objective function. Sassi et al. (2015) carried out a collaborative project with the French postal service. They studied an E-VRP with CSs of different technologies, a hybrid fleet made up of CVs and EVs of different types, compatibility constraints between the EVs and the charging technologies, time-dependent charging costs, and the option of partial recharging. They used a multi-start iterated tabu search based on large neighborhood search. Hiermann et al. (2016) introduced the E-FSMVRPTW in which the number and type of EVs are decision variables. They proposed an ALNS and a branch-and-price algorithm. Penna et al. (2016) solved the E-FSMVRPTW via a multi-start matheuristic. Their method employs ILS to generate a pool of high-quality routes that is then used in a set partitioning model to find an improved solution at each restart. Recently, Hiermann et al. (2017) have studied a new problem variant in which they consider PHVs, EVs, and CVs. They propose a hybrid genetic algorithm (HGA) enhanced with local search, large neighborhood search, and a set partitioning formulation. Their method relies on a layered route-evaluation procedure that depends on the type of vehicle used. If the route is performed by an EV the evaluation procedure includes the insertion of CSs, whereas if it is performed by a PHV the evaluation includes the selection of the fuel used.

2.2 Workforce scheduling and routing problem

In the workforce scheduling and routing problem (WSRP), a set of workers serves the requests of a set of geographically dispersed customers. The distinctive features of the WSRP are worker-request incompatibility constraints and request TWs; the former are usually related to the skills needed to serve each customer request. The WSRP encompasses several scheduling and routing problems arising in service industries. Examples include the technician routing and scheduling problem (TRSP), the home healthcare routing and scheduling problem (Cissé et al., 2017; Fikar & Hirsch, 2017), the routing of security personnel (Misir et al., 2011), and the scheduling of airport ground operations (Dohn et al., 2009).

The TRSP has applications in the field maintenance of telecoms and public utilities. To schedule the workforce at British Telecom, Tsang & Voudouris (1997) used the skill proficiency of each technician to estimate the time required to accomplish a given request. They proposed a guided local search to minimize a weighted combination of the traveling cost, overtime cost, and a penalty for unserved requests. Following a different modeling approach, Chen et al. (2016) studied a multi-period TRSP where the service time decreases as the technicians gain experience. Their experiments show that considering the learning effect leads to better solutions than those obtained under a static productivity assumption.

The TRSP has been extended in various directions. Bostel et al. (2008) present a multi-period TRSP for a water treatment and distribution utility, where the requests correspond to planned and emergency maintenance operations. There are no compatibility constraints between requests and technicians. They propose a column generation algorithm for instances with up to 100 requests and a memetic algorithm for larger instances. Pillac et al. (2013) studied an extension of the TRSP where the requests include requirements for spare parts and tools. The technicians can collect tools and spare parts from a central depot at any time during the execution of their routes. Pillac et al. propose a parallel matheuristic based on ALNS and a set covering formulation. Kovacs et al. (2012) propose an ALNS for a TRSP where the technicians have different proficiency levels for several skills and the requests require multiple technicians. The technicians are assigned to teams, and routes are designed for the teams.

Another common feature of the WSRP is the need to comply with working-time regulations. These regulations impose a working TW or a maximum duration for each route and (sometimes) mandatory breaks. When lunch breaks are necessary, they may have fixed TWs and be taken at customer locations (Kovacs et al., 2012; Coelho et al., 2016; Liu et al., 2017). Alternatively, they may be taken at specified locations such as restaurants (Bostel et al., 2008). In the TRSP-CEV we assume that lunch breaks can be taken anywhere in the route.

Our TRSP-CEV extends the literature on E-VRPs (with hybrid fleets of CVs and EVs) by including several additional characteristics related to service provision with heterogeneous workers. To the best of our knowledge, this is the first study that combines the elements of these two complex VRPs (E-VRP and WSRP) into a single rich VRP model.

3 Technician routing and scheduling problem with conventional and electric vehicles

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 CSs. Each station $s \in \mathcal{S}$ has a charging cost cc_s (in €$/min$). Each customer $i \in \mathcal{C}$ has a request needing skill k_i from set $\mathcal{K}$ and having a service time st_i and a TW $[ec_i, lc_i]$, where ec_i and lc_i are the earliest and latest possible service start times. For simplicity, in the remainder of this paper we use the terms customer and request interchangeably.

The set of technicians is denoted $\mathcal{T}$. Each technician $t \in \mathcal{T}$ has (i) a *fixed daily cost* fc_t (€/route); (ii) a subset of skills $\mathcal{K}_t \subseteq \mathcal{K}$; (iii) a shift $[es_t, ls_t]$, where es_t (resp. ls_t) is the technician's earliest departure time from (resp. latest return time to) the depot; (iv) a lunch break $[el_t, ll_t]$ where el_t and ll_t are the starting and ending time of the lunch break; and (v) an *energy consumption factor* cf_t. This factor scales the energy consumption of an EV according to the technician's driving style: sportive, normal, or eco (Bingham et al., 2012). Let $\mathcal{T}' \subseteq \mathcal{T}$ be the subset of technicians who work a partial shift without a lunch break. The technicians drive vehicles from a fixed fleet composed of CVs and EVs. The set of vehicles is $\mathcal{V} = \mathcal{V}_c \cup \mathcal{V}_e$, where $\mathcal{V}_c$ is the subset of CVs and $\mathcal{V}_e$ is the subset of EVs. Each vehicle $v \in \mathcal{V}$ has a travel cost tc_v (€$/km$). The vehicles $v \in \mathcal{V}_e$ also have a fixed cost gc_v for recharging (€/charge), a battery capacity Q_v (kWh), and a set $\mathcal{S}_v \subseteq \mathcal{S}$ of compatible CSs. Finally, $\mathcal{A} = \{(i, j) : i, j \in \mathcal{N}, i \neq j\}$ 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 EV $v \in \mathcal{V}_e$.

Similarly to Zündorf (2014) and Montoya et al. (2017), we model the SoC as a nonlinear function of the charging time. However, we use a discrete nonlinear approximation rather than the piecewise linear approximation; this allows us to easily capture the nonlinear behavior of the charging process. Moreover, it enables a simple translation of the results of the TRSP-CEV into practical charging decisions since the SoC in EVs is generally displayed as a rounded percentage of the battery capacity. Formally, to model the charging of EV $v \in \mathcal{V}_e$ at CS $s \in \mathcal{S}_v$ we use the function f_{sv} to describe the relation between the vehicle's charging time (in minutes) and the battery SoC (in % of Q_v). This function is $f_{sv} = \{(b, a_{svb}) | b \in B = \{0, 1, \ldots, 100\}\}$ where a_{svb} is the time to take the SoC from 0 to b% of Q_v at station $s \in \mathcal{S}_v$. In our model, we calculate the time to increase the SoC from l% to u% ($l, u \in B : l \leq u$) as $f_{sv}^{-1}(u) - f_{sv}^{-1}(l) = a_{svu} - a_{svl}$. Figure 1 illustrates the charging functions for an EV with a 16 kWh battery and three different charging technologies.

3.1 Mixed integer linear programming formulation of the TRSP-CEV

We now provide an MILP formulation of the TRSP-CEV. As in many E-VRP models (Felipe et al., 2014; Schneider et al., 2014; Montoya et al., 2017), to distinguish the individual visits to a CS we introduce a unique node for each potential visit. Accordingly, we define set $\mathcal{N}' = \{0\} \cup \mathcal{C} \cup \mathcal{S}'$, where set $\mathcal{S}'$ includes β copies of each CS $s \in \mathcal{S}$ (i.e., $|\mathcal{S}'| = \beta \times |\mathcal{S}|$). In the MILP we use the following decision variables: x_{ijvt} is equal to 1 if technician $t \in \mathcal{T}$ travels from node i to $j \in \mathcal{N}'$ in vehicle $v \in \mathcal{V}$, and 0 otherwise. Variable

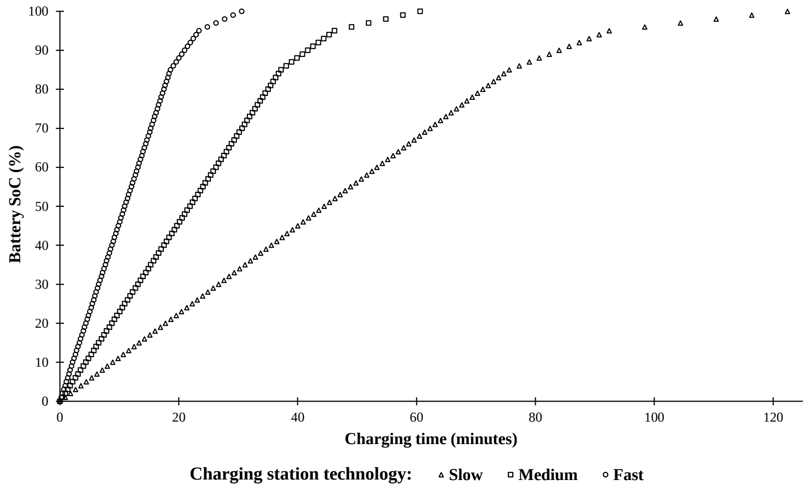

Figure 1: Discrete charging functions for an EV with a battery of 16 kWh using different charging technologies.

τ_{it} tracks the arrival time of technician $t \in \mathcal{T}$ at node $i \in \mathcal{N}'$. Variable y_{iv} tracks the SoC of EV $v \in \mathcal{V}_e$ upon departure from node $i \in \mathcal{N}'$. Variables q_{sv} and o_{sv} represent the SoC when $v \in \mathcal{V}_e$ arrives at and departs from CS $s \in \mathcal{S}_v^{'}$. Variable α_{svb} (resp. ρ_{svb}) is equal to 1 if the SoC is $b \in B$ when vehicle $v \in \mathcal{V}_e$ arrives at (resp. departs from) the CS $s \in \mathcal{S}_v^{'}$. Variable Δ_{sv} represents the time spent by vehicle $v \in \mathcal{V}_e$ at CS $s \in \mathcal{S}_v^{'}$. Variable w_{ijt} is equal to 1 if technician $t \in \mathcal{T}$ takes a lunch break between i and $j \in \mathcal{N}'$, and 0 otherwise. Variable z_{ijt} is equal to 1 if technician $t \in \mathcal{T}$ takes a lunch break after traveling from node i to $j \in \mathcal{N}'$, and 0 otherwise. Variable z'_{ijt} is equal to 1 if technician $t \in \mathcal{T}$ takes a lunch break before traveling from node i to $j \in \mathcal{N}'$, and 0 otherwise. The MILP formulation follows:

$$\text{Min} \sum_{j \in \mathcal{N}'} \sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}} fc_t \cdot x_{0jvt} + \sum_{i \in \mathcal{N}'} \sum_{\substack{j \in \mathcal{N}' \\ : j \neq i}} \sum_{v \in \mathcal{V}} \sum_{t \in \mathcal{T}} d_{ij} \cdot tc_v \cdot x_{ijvt} + \sum_{v \in \mathcal{V}_e} \sum_{s \in \mathcal{S}_v'} cc_s \cdot \Delta_{sv} + \sum_{i \in \mathcal{N}'} \sum_{v \in \mathcal{V}_e} \sum_{s \in \mathcal{S}_v'} \sum_{t \in \mathcal{T}} gc_v \cdot x_{isvt} \quad (1)$$

subject to:

$$\sum_{i\in\mathcal{N}'}\sum_{v\in\mathcal{V}}\sum_{\substack{t\in\mathcal{T}:\\k_j\in\mathcal{K}_t}} x_{ijvt} = 1, \qquad \forall j\in\mathcal{C} \tag{2}$$

$$\sum_{v\in\mathcal{V}}\sum_{t\in\mathcal{T}} x_{ijvt} \le 1, \qquad \forall i,j\in\mathcal{N}' \tag{3}$$

$$\sum_{j\in\mathcal{N}'}\sum_{t\in\mathcal{T}} x_{0jvt} \le 1, \qquad \forall v\in\mathcal{V} \tag{4}$$

$$\sum_{j\in\mathcal{N}'}\sum_{v\in\mathcal{V}} x_{0jvt} \le 1, \qquad \forall t\in\mathcal{T} \tag{5}$$

$$\sum_{j\in\mathcal{N}'} x_{jivt} - \sum_{j\in\mathcal{N}'} x_{ijvt} = 0, \qquad \forall i\in\mathcal{N}',\forall v\in\mathcal{V},\forall t\in\mathcal{T} \tag{6}$$

$$e_{ijv}\cdot cf_t\cdot x_{ijvt} - (1-x_{ijvt})\cdot Q_v \le y_{iv}-y_{jv}, \qquad \forall i\in\mathcal{N}',\forall j\in\mathcal{C},\forall v\in\mathcal{V}_e,\forall t\in\mathcal{T} \tag{7}$$

$$y_{iv}-y_{jv} \le e_{ijv}\cdot cf_t\cdot x_{ijvt} + (1-x_{ijvt})\cdot Q_v, \qquad \forall i\in\mathcal{N}',\forall j\in\mathcal{C},\forall v\in\mathcal{V}_e,\forall t\in\mathcal{T} \tag{8}$$

$$e_{isv}\cdot cf_t\cdot x_{isvt} - (1-x_{isvt})\cdot Q_v \le y_{iv}-q_{sv} \qquad \forall i\in\mathcal{N}',\forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'},\forall t\in\mathcal{T} \tag{9}$$

$$y_{iv}-q_{sv} \le e_{isv}\cdot cf_t\cdot x_{isvt} + (1-x_{isvt})\cdot Q_v, \qquad \forall i\in\mathcal{N}',\forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'},\forall t\in\mathcal{T} \tag{10}$$

$$y_{0v} = Q_v, \qquad \forall v\in\mathcal{V}_e \tag{11}$$

$$y_{iv} \ge e_{i0v}\cdot cf_t\cdot x_{i0vt}, \qquad \forall i\in\mathcal{N}',\forall v\in\mathcal{V}_e,\forall t\in\mathcal{T} \tag{12}$$

$$\sum_{i\in\mathcal{N}'} x_{isvt} \le 1, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'},\forall t\in\mathcal{T} \tag{13}$$

$$y_{sv} = o_{sv}, \qquad ,\forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{14}$$

$$q_{sv} \le o_{sv}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{15}$$

$$q_{sv} \le Q_v\cdot\sum_{i\in\mathcal{N}'}\sum_{t\in\mathcal{T}} x_{isvt}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{16}$$

$$o_{sv} \le Q_v\cdot\sum_{i\in\mathcal{N}'}\sum_{t\in\mathcal{T}} x_{isvt}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{17}$$

$$\frac{q_{sv}}{Q_v}\cdot 100 \ge \sum_{b\in B} b\cdot\alpha_{svb}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{18}$$

$$\frac{q_{sv}}{Q_v}\cdot 100 - 1 \le \sum_{b\in B} b\cdot\alpha_{svb}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{19}$$

$$\sum_{b\in B}\alpha_{svb} \le \sum_{i\in\mathcal{N}'}\sum_{t\in\mathcal{T}} x_{isvt}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{20}$$

$$\frac{o_{sv}}{Q_v}\cdot 100 \le \sum_{b\in B} b\cdot\rho_{svb}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{21}$$

$$\frac{o_{sv}}{Q_v}\cdot 100 + 1 \ge \sum_{b\in B} b\cdot\rho_{svb}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{22}$$

$$\sum_{b\in B}\rho_{svb} \le \sum_{i\in\mathcal{N}'}\sum_{t\in\mathcal{T}} x_{isvt}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{23}$$

$$\Delta_{sv} = \sum_{b\in B} a_{svb}\cdot\rho_{svb} - \sum_{b\in B} a_{svb}\cdot\alpha_{svb}, \qquad \forall v\in\mathcal{V}_e,\forall s\in\mathcal{S}_v^{'} \tag{24}$$

$$\begin{aligned}\tau_{it} + w_{ijt}\cdot(ll_t-el_t) + (tt_{ij}+st_i)\cdot x_{ijvt} - \\ (ls_t + (ll_t-el_t))\cdot(1-x_{ijvt}) \le \tau_{jt},\end{aligned} \qquad \forall v\in\mathcal{V}_e,\forall i\in\mathcal{C},\forall j\in\mathcal{N}',\forall t\in\mathcal{T} \tag{25}$$

$$\tau_{st} + w_{sjt} \cdot (ll_t - el_t) + \Delta_{sv} + tt_{sj} \cdot x_{sjvt} -$$
$$(a_{max} + ls_t + (ll_t - el_t)) \cdot (1 - x_{sjvt}) \le \tau_{jt}, \quad \forall v \in \mathcal{V}_e, \forall j \in \mathcal{N}', \forall s \in \mathcal{S}_v', \forall t \in \mathcal{T} \tag{26}$$
$$w_{ijt} \le \sum_{v \in \mathcal{V}} x_{ijvt}, \quad \forall i, j \in \mathcal{N}', \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{27}$$
$$\sum_{i \in \mathcal{N}'} \sum_{j \in \mathcal{N}'} w_{ijt} = \sum_{i \in \mathcal{N}'} \sum_{v \in \mathcal{V}} x_{0ivt}, \quad \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{28}$$
$$\tau_{it} + st_i \le \Big(el_t \cdot \sum_{j \in \mathcal{N}'} w_{ijt}\Big) + \Big(ls_t \cdot (1 - \sum_{j \in \mathcal{N}'} w_{ijt})\Big), \quad \forall i \in \mathcal{C}, \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{29}$$
$$\tau_{st} + \Delta_{sv} \le \Big(el_t \cdot \sum_{j \in \mathcal{N}'} w_{sjt}\Big) + \Big(ls_t \cdot (1 - \sum_{j \in \mathcal{N}'} w_{ijt})\Big), \quad \forall s \in \mathcal{S}_v', \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{30}$$
$$\tau_{it} \ge \Big(ll_t \cdot \sum_{j \in \mathcal{N}'} w_{jit}\Big) + \Big(es_t \cdot (1 - \sum_{j \in \mathcal{N}'} w_{jit})\Big), \quad i \in \mathcal{N}', \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{31}$$
$$el_t \cdot z_{ijt} - \tau_{it} - p_i + ls_t \cdot (1 - z_{ijt}) \ge tt_{ij} \cdot z_{ijt}, \quad \forall i, j \in \mathcal{N}', \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{32}$$
$$\tau_{jt} - ll_t \cdot z'_{ijt} \ge tt_{ij} \cdot z'_{ijt}, \quad \forall i, j \in \mathcal{N}', \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{33}$$
$$z_{ijt} + z'_{ijt} = w_{ijt}, \quad \forall i, j \in \mathcal{N}', \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{34}$$
$$\tau_{it} - tt_{0i} \ge es_t, \quad \forall i \in \mathcal{N}', \forall t \in \mathcal{T} \tag{35}$$
$$\tau_{it} + st_i + tt_{i0} \le ls_t, \quad \forall i \in \mathcal{C}, \forall t \in \mathcal{T} \tag{36}$$
$$\tau_{st} + \Delta_{sv} + tt_{s0} \le ls_t, \quad \forall v \in \mathcal{V}_e, \forall s \in \mathcal{S}_v', \forall t \in \mathcal{T} \tag{37}$$
$$ec_i \le \tau_{it} \le lc_i, \quad \forall i \in \mathcal{C}, \forall t \in \mathcal{T} \tag{38}$$
$$x_{ijvt} \in \{0,1\} \quad \forall v \in \mathcal{V}_e, \forall i, j \in \mathcal{C} \cup \{0\} \cup \mathcal{S}_v' : j \ne i, \forall t \in \mathcal{T} \tag{39}$$
$$x_{ijvt} \in \{0,1\} \quad \forall v \in \mathcal{V}_c, \forall i, j \in \mathcal{C} \cup \{0\} : j \ne i, \forall t \in \mathcal{T} \tag{40}$$
$$\alpha_{svb} \in \{0,1\}, \quad \rho_{svb} \in \{0,1\}, \quad \forall v \in \mathcal{V}_e, \forall s \in \mathcal{S}_v', \forall b \in B \tag{41}$$
$$\tau_{it} \ge 0, \quad \forall i \in \mathcal{N}', \forall t \in \mathcal{T} \tag{42}$$
$$y_{iv} \ge 0, \quad \forall i \in \mathcal{N}', \forall v \in \mathcal{V}_e \tag{43}$$
$$q_{sv} \ge 0, \quad o_{sv} \ge 0, \quad \Delta_{sv} \ge 0, \quad \forall v \in \mathcal{V}_e, \forall s \in \mathcal{S}_v', \tag{44}$$
$$w_{ijt} \in \{0,1\}, \quad z_{ijt} \in \{0,1\}, \quad z'_{ijt} \in \{0,1\}, \quad \forall i, j \in \mathcal{N}' : j \ne i, \forall t \in \mathcal{T} \setminus \mathcal{T}' \tag{45}$$

The objective function (1) minimizes the total cost given by the daily cost of the technicians, the total travel cost, and the charging costs of the EVs. Constraints (2) ensure that each customer is visited once by a technician with the appropriate skill. Constraints (3) ensure that each arc is used by at most one vehicle and technician. Constraints (4)–(5) ensure that only one technician is assigned to each vehicle (and vice versa). Constraints (6) impose flow conservation at all the nodes. Constraints (7)–(8) and (9)–(10) track the SoC of the EVs at customers and CSs respectively. Constraints (11) ensure that the EVs depart from the depot with fully charged batteries. Constraints (12) ensure that the EVs have enough energy to return to the depot. Constraints (13) ensure that an EV charges at most once at each CS copy. Constraints (14) set to o_{sv} the battery SoC of EV v upon departure from CS s. Constraints (15) couple the SoC when an EV arrives at and departs from any CS. Constraints (16) and (17) ensure that the SoC is bounded by the capacity of the battery when the EVs arrive at and depart from CSs. Constraints (18)–(23) define the SoC when the EVs arrive at or depart from CSs. Constraints (24) define the time spent charging at CSs. Constraints (25) and (26) track the arrival time at each node. In constraints (26), parameter a_{max} represents the maximum charging time of any charging function. Constraints (27) ensure that each technician takes a lunch break between two nodes visited in his/her route. Constraints (28) ensure that only scheduled technicians (i.e., those that leave the depot) take lunch breaks. Constraints (29)–(31) ensure that the technicians take their lunch breaks in the scheduled intervals. Constraints (32)–(34) ensure that the technicians take their lunch break either before or after traveling to a node. Note that for the technicians in $\mathcal{T}'$ we remove the w_{ijt}, z_{ijt}, and z'_{ijt} variables and omit constraints (27)–(34). Constraints (35)–(37) impose the schedule of the technicians. Constraints (38) ensure that every request is served within its TW. Finally, constraints (39)–(45) define the domain of the decision variables.

4 Parallel matheuristic

The TRSP-CEV belongs to the class of "rich" VRPs because it has multiple characteristics (Hasle & Kloster, 2007): a heterogeneous, fixed, and hybrid fleet (of EVs and CVs); EV energy constraints; customer TWs; request-technician compatibility constraints; technician availability constraints (schedule

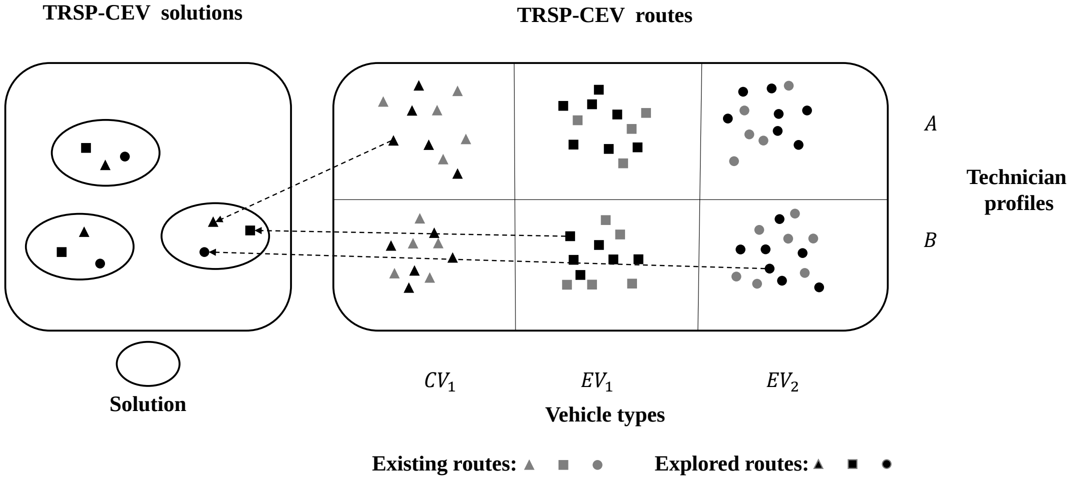

Figure 2: Decomposition scheme for TRSP-CEV.

and lunch breaks) and driving styles; and the assignment of technicians to vehicles. Solving the TRSP-CEV using classical metaheuristics may be difficult. For instance, neighborhood-based metaheuristics may spend considerable time exploring solutions that turn out to be infeasible. To overcome this, our solution method uses an alternative exploration approach. Instead of working directly on the space of TRSP-CEV solutions, we search a space made up of feasible TRSP-CEV routes. A feasible route is defined as a tuple containing: (i) a technician, (ii) a vehicle, (iii) a sequence of customers, whose requests are compatible with the technician's skills, and (eventually) a set of charging operations.

We follow the spirit of the approach of Taillard (1999) for heterogeneous-fleet VRPs (HVRPs). Taillard proposes what he calls a *heuristic column generation*. The algorithm solves one homogeneous VRP for each vehicle type and stores the routes in long-term memory. In a second stage, it selects a subset of stored routes to find a solution. The exploration of the routes can be parallelized for efficiency. Building on this idea, our matheuristic applies one of the fundamental decomposition strategies in parallel algorithm design: exploratory decomposition. This strategy partitions the search space into smaller regions and searches them concurrently (Grama et al., 2003). Therefore, we (i) partition the search space into subspaces that correspond to all possible combinations of vehicles and technicians; (ii) search each subspace in parallel to find a set of high-quality routes; (iii) build a TRSP-CEV solution by combining routes from different subspaces.

In practice, companies have multiple vehicles with the same characteristics and technicians with the same skills and schedules. To avoid exploring the same subspace repeatedly, we group vehicles and technicians with identical characteristics in $\mathcal{VT}$ and $\mathcal{TP}$, respectively. The set $\mathcal{VT}$ represents the *vehicle types*: $v' \in \mathcal{VT}$ represents $m_{v'}$ vehicles with the same characteristics (e.g., travel cost, battery capacity, and compatible CSs). Similarly, the set $\mathcal{TP}$ represents the *technician profiles*: $t' \in \mathcal{TP}$ represents $n_{t'}$ technicians with identical skills, driving style, schedule, and lunch break. Our matheuristic explores in parallel the $|\mathcal{TP}| \times |\mathcal{VT}|$ subspaces resulting from the Cartesian product $\mathcal{TP} \times \mathcal{VT}$. Figure 2 illustrates the decomposition scheme for a TRSP-CEV instance with one CV, two EVs of different types, and three technicians, one with profile A and two with profile B.

4.1 General structure

Algorithm 1 outlines the structure of our parallel matheuristic, PMa. The algorithm starts by calling (line 2) `groupTechnicians`$(\mathcal{T})$, which groups the technicians and generates the set $\mathcal{TP}$. It then (line 3) invokes `groupVehicles`$(\mathcal{V})$, which groups vehicles and generates the set $\mathcal{VT}$, and calls (line 4) `buildAssignments`$(\mathcal{TP}, \mathcal{VT})$. This procedure builds the set $\mathcal{P}$ containing all possible assignments of technician profiles to vehicle types. For each assignment $p \in \mathcal{P}$ PMa solves, on a dedicated thread, a VRP with TWs and lunch breaks (VRPTW-LB). Let $tp(p) \in \mathcal{TP}$ be the technician profile in assignment p and $vt(p) \in \mathcal{VT}$ the type of vehicle involved. In the VRPTW-LB for assignment p we assume that (i) we have an unlimited number of technicians with profile $tp(p)$, and (ii) the fleet is unlimited and composed only of vehicles of type $vt(p)$. If $vt(p)$ is an EV, then the resulting problem is an E-VRPTW-LB. We

Algorithm 1 Parallel matheuristic: General structure

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

use a GRASP to solve the VRPTW-LB or E-VRPTW-LB problems associated with the $|\mathcal{TP}| \times |\mathcal{VT}|$ assignments in $\mathcal{P}$. The algorithmic components depend on the type of problem being solved. The GRASP returns a set Ω_p containing all the routes of the local optima found during execution (line 7). The routes in Ω_p are added to the long-term memory structure Ω (line 8). After completing the parallel phase, PMa calls (line 10) `setCovering(`G`,`Ω`,`$\mathcal{TP}$`,`$\mathcal{VT}$`)`, which solves an extended set covering formulation over Ω to give a feasible TRSP-CEV solution. At this point we take into account the constraints on the numbers of technicians and vehicles.

4.2 Greedy randomized adaptive search procedure

GRASPs are metaheuristic algorithms that produce high-quality solutions to optimization problems via a two-phase strategy. The first phase builds diverse solutions via randomized constructive heuristics, and the second phase improves these solutions using local search (Resende & Ribeiro, 2016). Several of the state-of-the-art approaches for VRP variants are hybrid methods based on GRASP. For instance, Mendoza et al. (2016) tackled the VRP with stochastic demands using a hybrid metaheuristic based on GRASP and heuristic concentration. Haddadene et al. (2016) proposed a GRASP × ILS for a VRP arising in home healthcare with TWs, synchronization, and precedence constraints. In this section we present the components of the GRASP used by PMa to solve the (E-)VRPTW-LB. For simplicity, we focus on the VRPTW-LB; we explain in a separate section the additional elements needed for EV characteristics.

4.2.1 Building subproblem instances

Because of differences in, for example, technician skills or charging technologies, not all nodes are compatible with all technician profiles or vehicle types. In the GRASP, we first build a reduced (E)VRPTW-LB instance by removing from $\mathcal{N}$ the nodes that are incompatible with $tp(p)$ or $vt(p)$ according to the following rules:

Skill compatibility: We remove customers that are incompatible with technicians of profile $tp(p)$ (i.e., $i \in \mathcal{C} : k_i \notin \mathcal{K}_{tp(p)}$).

TW–schedule: We remove customers $i \in \mathcal{C}$ with $es_{tp(p)} + tt_{0i} > lc_i$ or $ec_i + st_i + tt_{i0} > ls_{tp(p)}$ because of their TW incompatibility with the schedule of technicians of profile $tp(p)$.

TW–break: We remove customers $i \in \mathcal{C}$ with their whole TW $[ec_i, lc_i]$ inside the lunch break of technicians of profile $tp(p)$ (i.e., $[ec_i, lc_i] \subset [el_{tp(p)}, ll_{tp(p)}]$).

Range: For EVs, we use the battery capacity $Q_{vt(p)}$ to remove from $\mathcal{C}$ all customers that are unreachable from the closest compatible CS or the depot (i.e., $i \in \mathcal{C} : min_{j \in \mathcal{S}_{vt(p)} \cup \{0\}} \{e_{jivt(p)} \cdot cf_{tp(p)}\} > Q_{vt(p)}$).

CS compatibility: Finally, for EVs, we include in $\mathcal{N}$ only the compatible CS $s \in \mathcal{S}_{vt(p)}$. For CVs, $\mathcal{N}$ does not include any CS.

Because of this node removal step, the compatibility constraints (between customers and technicians, and between EVs and CSs) do not have to be checked during the GRASP execution.

4.2.2 Greedy randomized construction

At each GRASP iteration, we generate initial solutions using a randomized version of the well-known I1 heuristic for the VRPTW (Solomon, 1987). This randomized Solomon heuristic (RSH) builds routes sequentially. After initializing a route with a randomly selected seed customer, RSH calculates the insertion cost of the remaining customers as follows:

$$c_1(i,u,j) = \omega_1 \cdot c_{11}(i,u,j) + \omega_2 \cdot c_{12}(i,u,j). \tag{46}$$

The insertion cost $c_1(i,u,j)$ of customer $u \in \mathcal{C}$ between two adjacent nodes i and j of the current partial route r has two terms: $c_{11}(i,u,j) = d_{iu} + d_{uj} - \mu \cdot d_{ij}$ is the change in the distance of route r; and $c_{12}(i,u,j) = t_{ju} - t_j$ is the change in the arrival time of customer j. In this expression, t_{ju} denotes the new arrival time at customer j, given that u is inserted into the route, and t_j is the arrival time before the insertion. The parameter $\mu > 0$ is the weight on the distance savings generated by the removal of arc (i,j) in the calculation of $c_{11}(i,u,j)$; and the parameters ω_1 and ω_2 are the weights on the two terms ($\omega_1 \geq 0, \omega_2 \geq 0, \omega_1 + \omega_2 = 1$). Using this insertion cost, RSH builds a restricted candidate list ($\mathcal{RCL}$) containing the κ customers with the smallest values of c_1. At each iteration, it selects randomly from $\mathcal{RCL}$ the next customer to be inserted into the current partial route. RSH inserts the selected customer (u) between customers i and j to minimize $c_2(i,u,j) = \lambda d_{0u} - c_1(i,u,j)$, with $\lambda \geq 0$. The parameter λ controls the extent to which the insertion position depends on the distance to the depot, and the extra distance and time needed to visit the unrouted customer in the current route.

The route construction stops when the end of the schedule of the technicians of profile $tp(p)$ is reached, and a new route is initialized if there are remaining unrouted customers. In the $\mathcal{RCL}$ we include only customers with feasible insertions: before evaluating (46), we check if inserting u between i and j satisfies the TW and schedule constraints. As observed by Pillac (2012), this feasibility check can be done in constant time using the concepts of *waiting time* (i.e., the time between the vehicle's arrival at i and the opening of the TW ec_i) and *forward time slack* (i.e., how long the departure time of a node can be delayed without causing the route to become infeasible). To efficiently calculate these values, we use the preprocessing and updating mechanisms of Savelsbergh (1992). Note that the lunch break of the technicians of profile $tp(p)$ has a fixed schedule $[el_{tp(p)}, ll_{tp(p)}]$. Therefore, when checking the feasibility of an insertion, we must verify the feasibility of the lunch schedule. We also have to take into account the time of the break when computing the waiting times and forward time slacks of the customers in the route. If necessary, to maintain the feasibility of the lunch break schedule, we change the nodes i and j between which the break is taken and adjust its location. We select whether, taking the break at node i before traveling to node j, or taking the break at j before starting the service leads to a feasible solution.

4.2.3 Local search

To improve the RSH solution, we use a variable neighborhood descent (VND; Hansen et al., 2017). This local search is a deterministic variant of VNS that sequentially explores several neighborhoods. For the VRPTW-LB we use two neighborhoods that focus on improving the routing decisions (i.e., relocate and exchange) and one neighborhood based on ejection chains that aims to reduce the number of routes. The relocate neighborhood removes a customer i from route $r = (0, \ldots, pred(i), i, suc(i), \ldots, 0)$ and inserts it between two consecutive nodes j and k in route $r' = (0, \ldots, j, k, \ldots, 0)$. The resulting routes are $\bar{r} = (0, \ldots, pred(i), suc(i), \ldots, 0)$ and $\bar{r}' = (0, \ldots, j, i, k, \ldots, 0)$. Similarly, the exchange neighborhood takes a pair of customers i and j served by routes $r = (0, \ldots, pred(i), i, suc(i), \ldots, 0)$ and $r' = (0, \ldots, pred(j), j, suc(j), \ldots, 0)$ and exchanges their positions. In this case the resulting routes are $\bar{r} = (0, \ldots, pred(i), j, suc(i), \ldots, 0)$ and $\bar{r}' = (0, \ldots, pred(j), i, suc(j), \ldots, 0)$. In our implementation we use intra-route ($r = r'$) and inter-route ($r \neq r'$) versions of both neighborhoods and a best-improvement exploration strategy. We again use the preprocessing and updating mechanisms of Savelsbergh (1992) to check the feasibility and cost improvement of these neighborhoods in constant time.

To decrease the value of the first term of the objective function (1), the third neighborhood of the VND aims to reduce the number of routes. Therefore, we sequentially apply a naive ejection chain (NEC) procedure (Rousseau et al., 2002) to all the routes in a given TRSP-CEV solution. To eliminate route r, NEC removes the customers in r one at a time. Let i be the removed or *floating* customer. After the removal, NEC tries to insert i into a route $r' \neq r$. If this fails, NEC searches for a customer j whose removal from r' would make the insertion of i possible. If such a customer exists, NEC removes j and inserts i into r'. The process restarts with j as the new floating customer. The ejection chain is completed when no floating customers exist (i.e., the removal and insertion processes succeed without ejecting a customer); in this case NEC continues with the ejection of the next customer in the sequence of route r. As observed by Rousseau et al. (2002), restrictions are necessary to (i) prevent NEC from cycling and (ii) increase its effectiveness (i.e., improve the probability of reducing the number of routes). First, we forbid the insertion of a floating customer into its original route r. Second, we keep a tabu list with the customers that have already been ejected and do not allow them to be ejected again. To control the increase in the distance of the solution, the floating customer is inserted into the route and position that minimizes the value of c_{11} as defined for the RSH (with $\mu = 1$). Finally, in the case where no ejection allows the insertion of the current floating customer (because it is infeasible or because the required ejection is tabu) the process stops for r and continues with the next route. If the NEC neighborhood removes one (or more routes) from the solution, the VND procedure goes back to the routing neighborhoods (i.e., relocate and exchange).

4.2.4 Dealing with electric vehicles

If $vt(p)$ is an EV, the routing problem solved in the parallel phase becomes an E-VRPTW-LB. To adapt our GRASP to the E-VRPTW-LB, we slightly modify the components of the RSH and VND. For instance, every time the RSH and the NEC neighborhood try to insert a customer into a route, we must check if the resulting route is energy-feasible. This check is executed in two stages. First, we drop any visits to CSs and check whether the route can be covered on a single battery charge (i.e., using $Q_{vt(p)}$ or less). If so, the insertion is energy-feasible. Otherwise, we repair the route using a greedy heuristic. We reject the insertion if the heuristic is unable to find a feasible route, i.e., a route that satisfies not only the energy constraint but also the TWs, lunch breaks, and schedule constraints. We carry out a similar procedure every time the relocate and exchange neighborhoods evaluate a move. We first drop any visits to CSs from the route(s) involved in the move and check the TWs, lunch breaks, and schedule constraints; second, we check if the move improves the solution; and third, we use a greedy heuristic to insert CSs in each route involved in the move. It is worth noting that a move that is infeasible or nonimproving on a route without CSs cannot be feasible or improving after we insert CSs.

To repair energy-infeasible routes we use a greedy heuristic based on those proposed by Felipe et al. (2014) and Montoya et al. (2017) for related E-VRPs. Let $\Pi = (\pi(0), \pi(1), ..., \pi(i), ..., \pi(j), ..., \pi(n_r))$ be an energy-infeasible route. Nodes $\pi(0)$ and $\pi(n_r)$ in Π represent the depot while nodes $\pi(1), ..., \pi(n_r - 1)$ represent the customers. Algorithm 2 outlines the structure of the heuristic. There are five procedures: `trackTimeVariables`$(\cdot)$, `trackBattery`$(\cdot)$, `sumNegative`$(\cdot)$, `totalCost`$(\cdot)$, and `copyAndInsert`$(\cdot)$. Procedure `trackTimeVariables`$(\cdot)$ computes the earliest departure time $D_{\pi(i)}$ and the latest feasible arrival times $L_{\pi(i)}$ at each node $\pi(i) \in \overline{\Pi}$ to ensure TW, lunch break, and schedule feasibility. Procedure `trackBattery`$(\cdot)$ computes the SoC $Y_{\pi(i)}$ at each node $\pi(i) \in \overline{\Pi}$. Note that since Π is an energy-infeasible route, $Y_{\pi(i)}$ may take negative values. Procedure `sumNegative`$(\cdot)$ computes the sum of the SoC with negative values (i.e., $sn = \sum_{\pi(i)\in\overline{\Pi}} min\{0, Y_{\pi(i)}\}$). Procedure `totalCost`$(\cdot)$ computes the total cost c of the route. Finally, procedure `copyAndInsert`$(\cdot)$ takes as input a fixed route, a CS, and a position in the route; it returns a copy of the fixed route with the CS inserted at the given position.

The heuristic starts by computing $D_{\pi(i)}$ and $L_{\pi(i)}$ for each node and the sum sn of the SoC with negative values for the current fixed-route $\overline{\Pi}$ (lines 2–7). It then enters the outer loop (lines 8–38). In each pass through the inner loop (lines 9–31), it (i) computes the slack time st at CS s_j between the vertices $\pi(i)$ and $\pi(i+1) \in \overline{\Pi}$ and determines if st is positive (lines 11–12), (ii) computes Y' and sn, given that the amount of charge at the inserted CS s_j is $min\{\psi(st), ec, Q_{vt(p)}\}$, where $\psi(st)$ is the amount of energy that the EV can charge in st time units, and ec is the energy needed to complete the fixed route from CS s_j, and (iii) selects the insertion that maximizes sn (lines 18–22). If $sn = 0$ (i.e., the route is energy-feasible), the heuristic selects the insertion (CS and position) that minimizes c, the cost of the route (lines 23–28). If there is at least one feasible insertion (i.e., insertion=true), then it performs the selected insertion (lines 32–34). When it does not find a feasible CS insertion, it stops, and the route is deemed infeasible (lines 35–36). If after the insertion of the CS, the route Π is still energy-infeasible (i.e., $sn < 0$), the heuristic starts again at line 9 and tries to insert additional CSs until energy-feasibility is reached or no more feasible insertions exist.

The choice of the heuristic to repair routes during the constructive and local search phases of our GRASP is based on computational performance. However, as Montoya et al. (2017) showed, optimal charging decisions are key to the effectiveness of E-VRP algorithms. We therefore run a global charging improvement (GCI) routine on the local optimum returned by the VND at the end of each GRASP iteration. In this routine we solve a fixed-route vehicle charging problem with time windows (FRVCP-TW) for each route in the solution. The FRVCP-TW finds the set of charging operations that minimizes the sum of the travel and charging costs of a fixed route while ensuring that (i) the SoC of the battery when the vehicle arrives at any node is nonnegative; (ii) the customers are visited within their TWs; (iii) the lunch break is taken at a valid time; and (iv) the whole route is performed within the technician's schedule.

Algorithm 2 Greedy heuristic

function GreedyHeuristic($\overline{\Pi}^0$,F)
    $\overline{\Pi} \longleftarrow \overline{\Pi}^0$
    $< D, L > \longleftarrow$ `trackTimeVariables(`$\overline{\Pi}$`)`
    $Y \longleftarrow$ `trackBattery(`$\overline{\Pi}$`)`
    $sn \longleftarrow$ `sumNegative(`Y`)`
    $c \longleftarrow \infty$
    insertion$\longleftarrow$ false
    while $sn < 0$ **do**
        for $j = 1$ to $|\mathcal{S}_{vt(p)}|$ **do**
            for $i = 0$ to $n_r - 1$ **do**
                $st \longleftarrow L_{\pi(i+1)} - D_{\pi(i)} - tt_{\pi(i)s_j} - tt_{s_j,\pi(i+1)}$
                if $st \geq 0$ **then**
                    $\overline{\Pi}' \longleftarrow$ `copyAndInsert(`$\overline{\Pi}, S_j, i$`)`
                    $Y' \longleftarrow$ `trackBattery(`$\overline{\Pi}'$`)`
                    $sn' \longleftarrow$ `sumNegative(`Y'`)`
                    $c' \longleftarrow$ `totalCost(`$\overline{\Pi}'$`)`
                    insertion$\longleftarrow$ true
                    if $sn' > sn$ **then**
                        $sn \longleftarrow s'$
                        $u \longleftarrow j$
                        $v \longleftarrow i$
                    end if
                    if $sn' = 0$ **and** $c' < c$ **then**
                        $sn \longleftarrow s'$
                        $c \longleftarrow c'$
                        $u \longleftarrow j$
                        $v \longleftarrow i$
                    end if
                end if
            end for
        end for
        if insertion= true **then**
            $\overline{\Pi} \longleftarrow$ `copyAndInsert(`$\overline{\Pi}', S_u, i$`)`
            $< D, L > \longleftarrow$ `trackTimeVariables(`$\overline{\Pi}$`)`
        else
            return false, $\overline{\Pi}$
        end if
    end while
    return true, $\overline{\Pi}$
end function

The GCI procedure is as follows. For each route visiting at least one CS, we (i) drop all the CSs, (ii) build an MILP for the FRVCP-TW, and (iii) solve the MILP using a commercial solver. We omit steps (ii) and (iii) for routes that are energy-feasible after dropping the CSs. A presents the detailed MILP formulation of the FRVCP-TW.

Figure 3 summarizes the two versions of the GRASP. For the E-VRPTW-LB the figure indicates how charging decisions are made: with the heuristic (H) or the MILP (M).

4.3 Set covering

To find a feasible TRSP-CEV solution, we solve an extended set covering (SC) formulation (line 10 of Algorithm 1) over the routes stored in Ω. We introduce the following parameters: c_r is the cost of route $r \in \Omega$ (including the technician, traveled distance, and charging costs); λ_{ri} is equal to 1 if route $r \in \Omega$ serves customer $i \in \mathcal{C}$ and 0 otherwise; $\xi_{rv'}$ is equal to 1 if route $r \in \Omega$ is performed with a vehicle of type $v' \in \mathcal{VT}$ and 0 otherwise; and $\eta_{rt'}$ is equal to 1 if route $r \in \Omega$ is performed by a technician of profile $t' \in \mathcal{TP}$ and 0 otherwise. Let χ_r be a binary decision variable that takes the value 1 if route $r \in \Omega$ is selected in the TRSP-CEV solution, and 0 otherwise. We formulate the SC as follows:

$$\min \sum_{r \in \Omega} c_r \cdot \chi_r \tag{47}$$

subject to

$$\sum_{r \in \Omega} \lambda_{ri} \cdot \chi_r \geq 1, \qquad \forall i \in \mathcal{C} \tag{48}$$

$$\sum_{r \in \Omega} \xi_{rv'} \cdot \chi_r \leq m_{v'} \qquad \forall v' \in \mathcal{VT} \tag{49}$$

$$\sum_{r \in \Omega} \eta_{rt'} \cdot \chi_r \leq n_{t'} \qquad \forall t' \in \mathcal{TP} \tag{50}$$

$$\chi_r \in \{0, 1\} \qquad \forall r \in \Omega \tag{51}$$

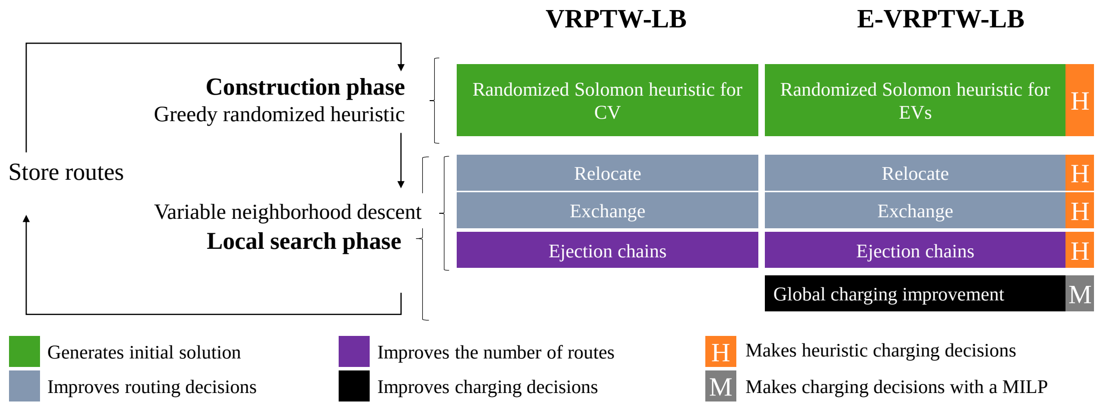

Figure 3: General structure of GRASP for (E-)VRPTW-LB.

The objective function (47) minimizes the total cost. Constraints (48) ensure that each customer is served at least once. Constraints (49) impose the maximum number of vehicles of each type. Constraints (50) impose the maximum number of technicians of each profile. Finally, constraints (51) define the domain of the decision variables. Since the requests must be served exactly once, a set partitioning formulation may seem more appropriate. However, as observed by Pillac et al. (2013) for a similar problem, finding a good combination of routes that visit all the customers exactly once could be complex. Therefore, we use an SC formulation. If the solution includes duplicate visits to customers, we repair it as follows. For each customer with multiple visits, we enumerate the solutions resulting from keeping the customer in one route and removing it from the others. Then, we retain the solution with the lowest cost. Since we select the customers sequentially, our repair procedure is a heuristic.

5 Computational experiments

Since the TRSP-CEV is a new problem, there are no results or algorithms to benchmark against. Therefore, we first compare its performance to that of state-of-the-art approaches for the E-FSMVRPTW. We also run PMa on a set of industrial instances of the TRSP-CEV to gain insight into the impact of the fleet composition (i.e., proportion of EVs) on the solution cost and structure. The details of these experiments follow.

5.1 Implementation and experimental environment

We implemented PMa in Java (jdk-1.8.0_152) and used Gurobi Optimizer (version 7.5.2) to solve the MILPs in the GCI and SC phases. We used a computer with an Intel Xeon E5-2670 processor (with 16 cores at 2.6 GHz) and 64 GB of RAM running Linux CentOS 6.6. To parallelize our method we used the Java package `concurrent` (Oracle, 2017). More precisely, we implemented the GRASP tasks as a `Callable` object and used a `ThreadPoolExecutor` to manage and schedule the $|\mathcal{TP}| \times |\mathcal{VT}|$ tasks. We solved the SC formulation with a time limit of 800 s. If $|\mathcal{TP}| \times |\mathcal{VT}|$ was smaller than the number of available processors we duplicated some of the tasks (prioritizing those solving the E-VRPTW-LB) to better exploit the parallel design of the matheuristic.

The parameters of PMa are the number of GRASP iterations (ι), the size of the restricted candidate list (κ), the value μ used in the calculation of c_{11}, the weights of the two terms in the RHS insertion cost (ω_1 and ω_2), and the value of λ used in the calculation of c_2. To fine-tune these parameters we conducted a short computational study; for the sake of brevity we do not discuss the study in this paper. The values obtained are $(\iota, \kappa, \mu, \omega_1, \omega_2, \lambda) = (100, 10, 20.0, 0.1, 0.9, 3.0)$. For the best trade-off between solution quality and computational performance we set $\iota = 100$. This may seem small, but the GRASP component runs ι iterations for each assignment in $\mathcal{P}$ to feed the pool of routes Ω_p. Therefore, the total number of GRASP iterations is $\iota \times |\mathcal{P}|$.

5.2 Results for E-FSMVRPTW

For validation purposes, we adapted PMa to solve the closely related E-FSMVRPTW introduced by Hiermann et al. (2016). This problem routes an unlimited heterogeneous fleet of EVs to serve a set of geographically scattered customers within their TWs. The customers have a positive demand, the EVs have a limited capacity, all the CSs have the same technology, the EVs charge fully at CSs, the charging function is linear, and the EVs have a fixed operation cost. The E-FSMVRPTW minimizes the sum of the fixed cost of using the vehicles and the total traveled distance. To solve the E-FSMVRPTW with PMa, we included the customer demand and added the vehicle capacities as an additional GRASP constraint. We also modified the charging model to take into account the (simplified) linear modeling considered by Hiermann et al. (2016). Moreover, to ensure the parallel execution of our method, we included several dummy technicians for each vehicle type in the heterogeneous fleet. Finally, we dropped the lunch break and the technician/request compatibility constraints. We do not aim to establish new state-of-the-art results for the E-FSMVRPTW; we simply want to show that PMa can be competitive on a related problem with only mild modifications.

Hiermann et al. (2016) generated a set of 108 small instances with 5 to 15 customers and a set of 168 large instances with 100 customers and 21 CSs. The latter are based on the instances for the E-VRPTW from Schneider et al. (2014) extended with the fleet composition of Liu & Shen (1999) for the FSMVRPTW with CVs. These instances have different customer location patterns: randomly distributed (r), clustered (c), or a mix of both (rc). With respect to the planning horizon, the testbed has two types of instances: the first has a short horizon (type r1, c1, and rc1), and the second has a long horizon (type r2, c2, and rc2). Hiermann et al. (2016) consider three (increasing) battery capacities for each instance to produce data sets A, B, and C respectively.

To solve the E-FSMVRPTW, Hiermann et al. (2016) proposed an ALNS and a branch-and-price (BnP). For the small instances, their BnP was able to obtain the optimal solution within a time limit of two hours. Hiermann et al. (2017) solved only the large E-FSMVRPTW instances with their HGA. We compare the PMa results with both methods. Tables 1 and 2 summarize the results of the comparison on the small and large E-FSMVRPTW instances respectively. The results are computed over ten runs. For the small instances, we compare the results obtained by ALNS and PMa with the optimal solutions obtained by BnP. For the large instances, we compare the results with the best known solution (BKS) taken from Hiermann et al. (2016) or Hiermann et al. (2017) and updated with the new BKSs from PMa. The tables report four metrics: the number of optimal solutions or BKSs found by each method, the average gap with respect to the BKS or optimal solution ($\underline{S}$)[1], the average best gap (i.e., the average gap between the best solution found by a given method and $\underline{S}$), and the average running time in minutes. B.1 reports the detailed results for the E-FSMVRPTW.

Table 1: Comparison of PMa with ALNS of Hiermann et al. (2016) on small E-FSMVRPTW instances.

Metric	**ALNS**	**PMa**
Number of optimal solutions	108/168	81/168
Avg. Gap (%)	0.55	0.32
Avg. Best Gap (%)	0.00	0.31
Avg. Time (min)	0.32	0.06

Table 2: Comparison of PMa with ALNS (Hiermann et al., 2016) and HGA (Hiermann et al., 2017) on large E-FSMVRPTW instances.

Metric	**ALNS**	**HGA**	**PMa**
Number of BKS	22/168	119/168	32/168
Avg. Gap (%)	1.41	0.44	1.74
Avg. Best Gap (%)	0.48	0.10	1.35
Avg. Time (min)	22.66	15.80	11.78

On the small instances, PMa was competitive with ALNS. Although PMa matched only 81 optimal solutions, its average gap is smaller than that of ALNS (0.32% vs 0.55%). On the large instances (Table 2), PMa had an average gap (1.74%) greater than those of ALNS (1.41%) and HGA (0.44%). However, PMa found 25 new BKSs and matched another 7. To better indicate the performance of PMa, Table 3 presents average gaps and average best gaps for each instance type. It shows that PMa performs well on

[1] $Gap = \frac{cost(solution) - cost(\underline{S})}{cost(\underline{S})} \times 100$, where $\underline{S}$ is the optimal solution or the BKS.

Table 3: Performance of PMa for each instance type

Type		Avg. best gap (%)	Avg. gap (%)	Type		Avg. best gap (%)	Avg. gap (%)	Type		Avg. best gap (%)	Avg. gap (%)	Type		Avg. best gap (%)	Avg. gap (%)
	c1	0.04	0.09		c1	0.09	0.23		c1	0.10	0.26		c1	0.07	0.20
	c2	0.07	0.21		c2	0.18	0.31		c2	0.24	0.36		c2	0.16	0.29
A	r1	0.00	0.06	B	r1	0.08	0.30	C	r1	0.18	0.36	All	r1	0.09	0.24
	r2	2.39	2.89		r2	5.87	7.11		r2	7.21	8.47		r2	5.16	6.16
	rc1	0.12	0.28		rc1	0.23	0.39		rc1	0.24	0.39		rc1	0.19	0.35
	rc2	0.31	0.65		rc2	2.40	3.33		rc2	2.62	3.53		rc2	1.77	2.50

most instance types, with average gaps below 0.7%. The notable exceptions are the instances r2 and rc2. PMa, intended for a highly constrained E-VRP, does not perform well on these less-constrained instances with long planning horizons and randomly distributed customers.

PMa is much faster than ALNS on the small instances. On the large instances, PMa reports running times that are better than those of ALNS and HGA. This result must be interpreted with caution. First, there are slight differences in the computational environment used to evaluate the three methods. Second, while PMa exploits the now-standard multi-core technology, neither Hiermann et al. (2016) or Hiermann et al. (2017) explicitly state whether or not their implementations take advantage of this feature.

In conclusion, the results of our experiments on the E-FSMVRPTW suggest that PMa, with only mild modifications, gives competitive results for this closely related problem. This is encouraging, since the method was not developed for this problem.

5.3 Results for industrial TRSP-CEV instances

We generated a set of instances for the TRSP-CEV using data provided by the French electricity giant ENEDIS. We used these instances to conduct several experiments. We first used a set of small instances to compare the PMa results to optimal solutions found using the MILP formulation introduced in Section 3.1. In the second experiment, we compared the performance of PMa to that of the company's commercial routing software on industrial instances with a 100% CV fleet. Finally, in the third experiment we used the large instances to analyze different fleet composition scenarios and evaluate the impact of introducing EVs.

5.4 Instance generation

The maintenance and repair operations at ENEDIS are divided into geographical zones. Each zone has a depot where the technicians start and end their routes. We received access to 14 data sets classified according to the type of geographical zone: 4 urban, 5 semi-urban, and 5 rural instances (the naming convention indicates this information). The number of customers ranges between 54 and 167. The location, TWs, service time, and required skills of the requests come directly from ENEDIS data. To complete the instances, we added the actual CSs located in the geographical zone of the customers. We obtained the CS locations and technology (i.e., protocol and charging mode) from www.data.gouv.fr, the open-data platform of the French government (Quest, 2014). For the distances and travel times, we used real road-network data provided by Open Street Maps. To compute the nominal energy consumption for each arc, we used the model proposed by De Cauwer et al. (2015). This model considers fine-grained information on the roads (e.g., distance, speed, and elevation) and real EV parameters (e.g, mass and rolling resistance). We obtained the former from Open Street Maps and NASA (SRTM) and the latter from technical sources and specialized websites (Automobile-propre, 2017; Renault, 2014; Peugeot, 2015; Uhrig et al., 2015).

In our instances, the number of available technicians ranges between 9 and 12. There are two skills (electricity and gas). The technician profiles (skills, schedule, lunch break, etc.) correspond to real data. For confidentiality reasons, we scaled the costs while keeping the cost structure and magnitudes. The fleet is composed of one type of CV (Renault Kangoo) and two types of EVs (Renault Kangoo ZE and Peugeot Ion). Note that the travel cost of the CVs is much higher than that of the EVs (1 vs. 0.08 and 0.06 €/km, respectively). For each instance, we consider six scenarios with the percentage of EVs set to {0%, 20%, 40%, 60%, 80%, 100%}.

To compare the PMa results with optimal solutions, we generated a set of ten small instances with five and ten customers and two or three technicians and vehicles. These instances can be solved using the MILP formulation. To generate each small instance, we randomly selected customers, technicians, and vehicles from a randomly chosen large instance (ensuring that at least one vehicle is an EV). Our instances are publicly available at www.vrp-rep.org (Mendoza et al., 2014).[2]

5.4.1 Results for small TRSP-CEV instances

Initially, we solved the ten small TRSP-CEV instances using Gurobi and PMa. B.2 presents detailed results. PMa consistently matched the optimal solution found by Gurobi. Comparing the running times reveals the difficulty of solving the TRSP-CEV to optimality. While Gurobi took (on average) 7356.94 s, PMa took only 0.73 s. Moreover, the average running time of Gurobi rises from 186.00 s to 14527.88 s when the instance size increases from five to ten customers. It is thus safe to conclude that solving the MILP formulation for larger instances using a commercial optimizer would lead to excessive running times. These results support the choice of a matheuristic for large TRSP-CEV instances.

5.4.2 Comparison with current tool

We compared the performance of PMa to that of the current routing software (CRS) used by ENEDIS on our 14 instances. For confidentiality reasons we do not reveal the name of the tool or report detailed results. Since the CRS cannot deal with EVs, we considered only CVs. For each instance, ENEDIS provided us with the CRS solution for one run. We ran PMa 10 times on each instance, and we obtained better solutions on each run. Moreover, PMa reported an average gap of 2.08%, while this figure was 8.51% for CRS. In terms of running time, PMa reported an average of 14.96 min (with a range of 1.17 min to 21.46 min). Unfortunately we did not have access to the CRS running times.

5.4.3 Impact of fleet composition

ENEDIS is currently starting the transition from a fleet of CVs to a hybrid fleet of CVs and EVs. This process raises a number of managerial questions regarding the fleet composition and the best EV strategies. To help answer these questions, we analyzed the impact of the fleet composition and the access to charging infrastructure on the feasibility and quality of the TRSP-CEV solutions. We explore six scenarios with the proportion of EVs in the fleet ranging from 0% to 100%. For each instance and fleet composition we run PMa 10 times and report the average results. We analyze the data using three metrics that are important to ENEDIS: the number of routes, the total cost, and the total CO_2 emissions.

We first analyze the behavior of these metrics as the proportion of EVs in the fleet grows. Figure 4 shows the average cost for each instance and fleet composition. The fixed costs correspond to the first term of Equation (1) (the daily technician cost, which depends solely on the number of routes), and the variable cost corresponds to the other three terms (the total distance and charging costs). The value NF indicates that PMa did not find a feasible solution for that case (e.g., all rural instances when the fleet is entirely composed of EVs). Notice that a pathological case arises for `rural_21`. A closer look reveals that the customers are scattered over a large geographical region, so the EVs need frequent charging. Charging is time-consuming, so the resulting routes are long (in terms of travel time) and difficult to match to the technicians' availability.

The data on the fixed costs reported in Figure 4 shows unexpected behavior. Intuitively, when the fleet is composed mainly of EVs more routes are needed to serve the customers. This is because the EVs spend a portion of their available time on charging operations. However, for our instances, the number of routes is constant across the different fleet compositions. A more intuitive result comes from the data on the variable costs. As Figure 4 shows, the variable costs decrease as the proportion of EVs increases. This can be explained by the considerably higher cost per kilometer for CVs. Note that variable costs are higher for rural instances than for semi-urban and urban instances; this is because rural routes travel greater distances. The average traveled distance per served customer is 9.52 km on the rural instances compared to 3.74 km and 1.94 km for the semi-urban and urban instances, respectively.

Figure 5 shows the CO_2 emitted (on average) by the CVs for each instance and fleet composition. These values were calculated by multiplying the distance traveled by the CVs by the constant emission rate given in their technical information. As expected, the emissions decrease as the proportion of EVs increases. Rural instances have the greatest potential for emission reductions because the vehicles travel further. In some urban and semi-urban instances this metric decreases to zero before the EV proportion reaches 100%. This is because the solution does not use any CVs if the number of EVs suffices to serve all the customers.

[2]The instances will be made available after the conclusion of the reviewing process.

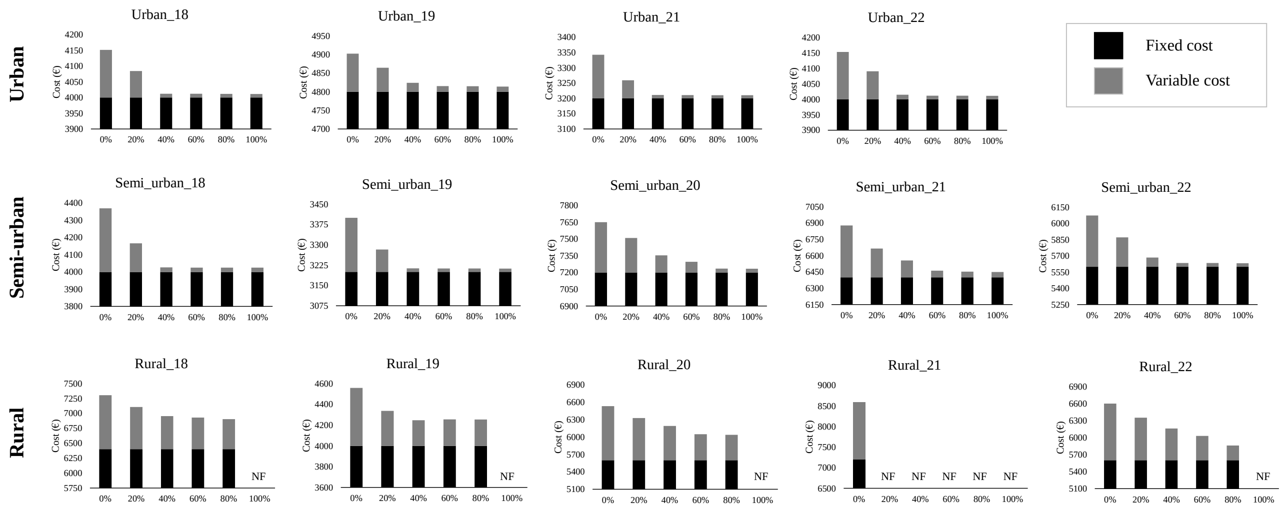

Figure 4: Average cost for each instance and fleet composition.

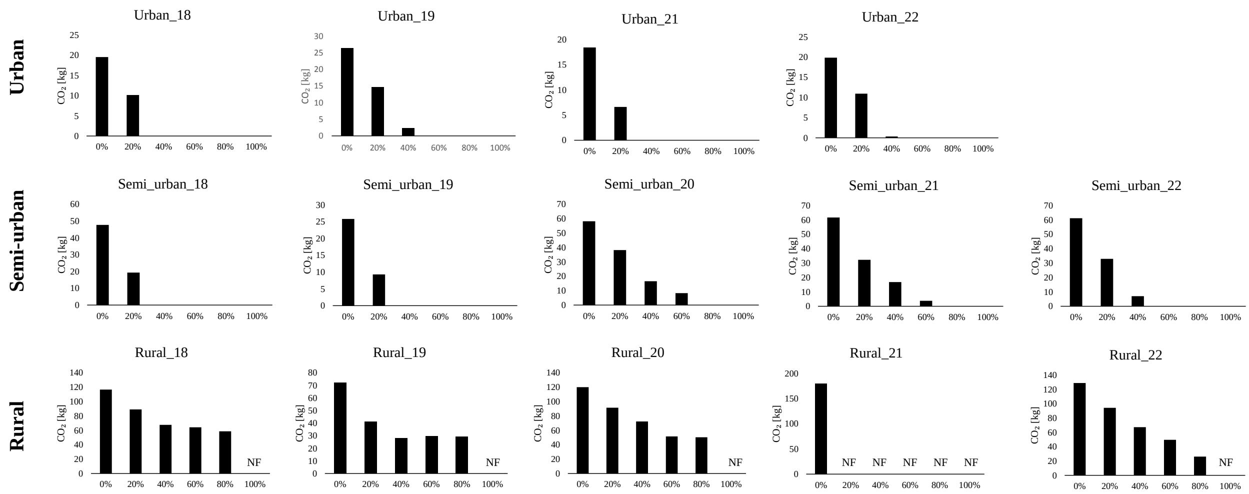

Figure 5: Average emission (in kg of CO_2) for each instance and fleet composition.

Table 4: Increase in metrics when en-route charging is forbidden (in %). ◇: the routes of the previous solution did not visit CSs in this scenario.

	EV percentage in the fleet								
	40%			60%			80%		
Instance	Routes	d_{CV}	Cost	Routes	d_{CV}	Cost	Routes	d_{CV}	Cost
rural_19		◇		0.00	9.32	0.10	0.00	11.79	0.30
rural_22	0.00	15.92	1.19	0.00	58.65	3.57	14.29	78.18	16.26

5.4.4 Impact of en-route charging

ENEDIS does not currently own charging infrastructure outside their depots. Since the availability of public stations is uncertain, the company prefers to avoid en-route charging. We therefore evaluated the impact of disallowing en-route charging on the cost and structure of the best TRSP-CEV solutions. In the previous experiments, the urban and semi-urban routes can be covered on a single battery charge (i.e, without en-roue charging). Moreover, only some rural solutions include en-route charging for EV percentages above 20% (`rural_19` and `rural_22`). Therefore, we ran PMa on these rural instances with 40% to 80% of EVs in the fleet, assuming that the EVs depart from the depot with a full battery and forbidding en-route recharging. We compared these results to those reported in Figure 4. We obtained feasible solutions for these instances in all cases. Table 4 shows the increase in the three metrics (number of routes, total distance traveled by the CVs (d_{CV}), and total cost) when en-route charging is forbidden[3]. Our results suggest that this has an important impact on the structure of the solutions. They may have more routes, and the CVs have to visit more customers to compensate for the limited range of EVs. Consequently, the cost increases. Table 4 shows that the number of routes is usually the same, but for `rural_22` the solution has an additional route when 80% of the fleet are EVs (this explains the large cost increase for this scenario). The cost increase usually comes from the greater distance traveled by the CVs. Finally, an important increase in the distance traveled by the CVs is observed in both instances. This behavior implies a similar increase in the CO_2 emissions, reducing the environmental benefits of the introduction of EVs.

6 Conclusions

We have introduced the technician routing and scheduling problem with conventional and electric vehicles (TRSP-CEV). The TRSP-CEV routes a set of technicians to serve a set of customers, using a hybrid fleet composed of EVs and CVs. We considers real-world constraints such as customer TWs; technician skills, schedules and lunch breaks; skill compatibility between technicians and requests; incompatibility between CSs and EVs; nonlinear charging behavior for EVs; and a limited number of vehicles. The problem requires simultaneous decisions about the vehicle-to-technician assignment, the sequencing of customers, and the EV battery charging (i.e., when and how much to charge).

To solve the TRSP-CEV we proposed PMa, a parallel matheuristic. The approach decomposes the TRSP-CEV into a set of (electric) VRPs with TWs and lunch breaks and solves each subproblem in parallel using a GRASP. PMa then uses an extended set covering model to find a TRSP-CEV solution using the routes of the local optima found by GRASP. PMa is competitive with state-of-the-art methods for the closely related E-FSMVRPTW. We built a set of realistic TRSP-CEV instances using data fom a French utility. Using these instances and our algorithm, we conducted computational experiments to analyze the impact of the fleet composition (proportion of EVs and CVs) on the costs and emissions. Our analysis shows that augmenting the proportion of EVs in the fleet does not necessarily increase the number of routes needed to serve the customers, but it does lead to a significant reduction in cost and emissions. Our experiments also showed that forbidding en-route recharging reduces the cost savings and environmental benefits that can be obtained by introducing EVs.

Future research may include the extension of the TRSP-CEV to consider the location decisions of the CSs; and the application of PMa to other VRPs that are amenable to solution-space decomposition (e.g., other workforce scheduling and routing problems).

[3]For all metrics the increase is calculated via $Increase(\%) = \frac{value(S_{wout})-value(S_{with})}{value(S_{with})} \times 100$, where S_{with} is the solution with en-route charging and S_{wout} is the solution without this operation.

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A MILP formulation of the fixed-route vehicle recharging problem with TWs

This appendix provides the MILP formulation of the FRVCP-TW that we solve in the GCI routine. Recall that $\Pi = (\pi(0), \pi(1), ..., \pi(i), ..., \pi(j), ..., \pi(n_r))$ is a route violating the energy constraint (i.e., for at least one of the nodes the SoC on arrival is negative) that is obtained after dropping the charging operations. Nodes $\pi(0)$ and $\pi(n_r)$ in Π represent the depot while nodes $\pi(1), ..., \pi(n_r - 1)$ represent the customers. The feasibility of Π may be restored by inserting detours to CSs. Since route Π is performed by a technician of profile $tp(p)$, we consider as fixed the time and location of the lunch break. To fix this, we create a dummy node $\pi(l)$ with a TW $[el_{tp(p)}, ll_{tp(p)}]$ and a service time $st_l = ll_{tp(p)} - el_{tp(p)}$. Moreover, let $\pi(l-1)$ and $\pi(l+1)$ be the customers served right before and after the lunch break in the original route. Then, we define $\overline{\Pi} = (\pi(0), ..., \pi(l-1), \pi(l), \pi(l+1), ..., \pi(n_r))$ to be the route that includes the dummy node $\pi(l)$. If the technician takes the lunch break before traveling from $\pi(l-1)$ to $\pi(l+1)$ in the original route, we fix it via $d_{\pi(l-1)\pi(l)} = 0$, $tt_{\pi(l-1)\pi(l)} = 0$, $e_{\pi(l-1)\pi(l)vt(p)} = 0$, and $d_{\pi(l)\pi(l+1)} = d_{\pi(l-1)\pi(l+1)}$, $tt_{\pi(l)\pi(l+1)} = tt_{\pi(l-1)\pi(l+1)}$, $e_{\pi(l)\pi(l+1)vt(p)} = e_{\pi(l-1)\pi(l+1)vt(p)}$. Moreover, we connect the dummy node l to the CSs using the data (i.e., energy consumption and travel time of the arcs) of node $l-1$ to take into account the possibility of recharging before or after the lunch break. If instead the technician takes the lunch break after traveling from $\pi(l-1)$ to $\pi(l+1)$, then we set $d_{\pi(l-1)\pi(l)} = d_{\pi(l-1)\pi(l+1)}$, $tt_{\pi(l-1)\pi(l)} = tt_{\pi(l-1)\pi(l+1)}$, $e_{\pi(l-1)\pi(l)vt(p)} = e_{\pi(l-1)\pi(l+1)vt(p)}$, and $d_{\pi(l)\pi(l+1)} = 0$, $tt_{\pi(l)\pi(l+1)} = 0$, $e_{\pi(l)\pi(l+1)vt(p)} = 0$. Similarly, we connect the dummy node l using the data of node $l+1$ to include the charging operation before or after the break. Figure 6 illustrates an FRVCP-TW for a route with three customers and three available CSs. This figure shows how we fix the lunch break when it is taken before traveling from $l-1$ to $l+1$. Note also that we allow only one visit to CSs between any two customers.

We use the following decision variables: variable $\varepsilon_{\pi(i)s}$ is equal to 1 if the vehicle charges at CS $s \in \mathcal{S}_{vt(p)}$ before visiting node $\pi(i) \in \overline{\Pi}$. Variable $\phi_{\pi(i)}$ tracks the SoC of the vehicle. If $\sum_{s \in \mathcal{S}_{vt(p)}} \varepsilon_{\pi(i)s} = 0$, $\phi_{\pi(i)}$ is the SoC when the EV arrives at node $\pi(i)$. On the other hand, if there exists an $s \in \mathcal{S}_{vt(p)}$ such that $\varepsilon_{\pi(i)s} = 1$, $\phi_{\pi(i)}$ is the SoC when the vehicle arrives at CS s right before visiting node $\pi(i)$. Variable $\gamma_{\pi(i)s}$ represents the energy charged at CS $s \in \mathcal{S}_{vt(p)}$ before visiting node $\pi(i) \in \overline{\Pi}$. Variables $q_{\pi(i)s}$ and $o_{\pi(i)s}$ represent the SoC when the EV arrives at and departs from CS $s \in \mathcal{S}_{vt(p)}$ before visiting node $\pi(i) \in \overline{\Pi}$. Variables $\alpha_{\pi(i)sb}$ and $\rho_{\pi(i)sb}$ are equal to 1 if the SoC is $b \in B$ when the EV arrives at and departs from the CS $s \in \mathcal{S}_{vt(p)}$ before visiting node $\pi(i) \in \overline{\Pi}$, respectively. Variable $\delta_{\pi(i)s}$ represents the time spent charging at CS $s \in \mathcal{S}_{vt(p)}$ before visiting node $\pi(i) \in \overline{\Pi}$. Variable $\tau_{\pi(i)}$ represents the arrival time at node $\pi(i) \in \overline{\Pi}$. The MILP formulation is:

$$\min \sum_{\pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}} \sum_{s \in \mathcal{S}_{vt(p)}} \Big(tc_{vt(p)} \cdot (d_{\pi(i-1)s} + d_{s\pi(i)} - d_{\pi(i-1)\pi(i)}) \cdot \varepsilon_{\pi(i)s} + gc_{vt(p)} \cdot \varepsilon_{\pi(i)s} + cc_s \cdot \delta_{\pi(i)s} \Big) \tag{52}$$

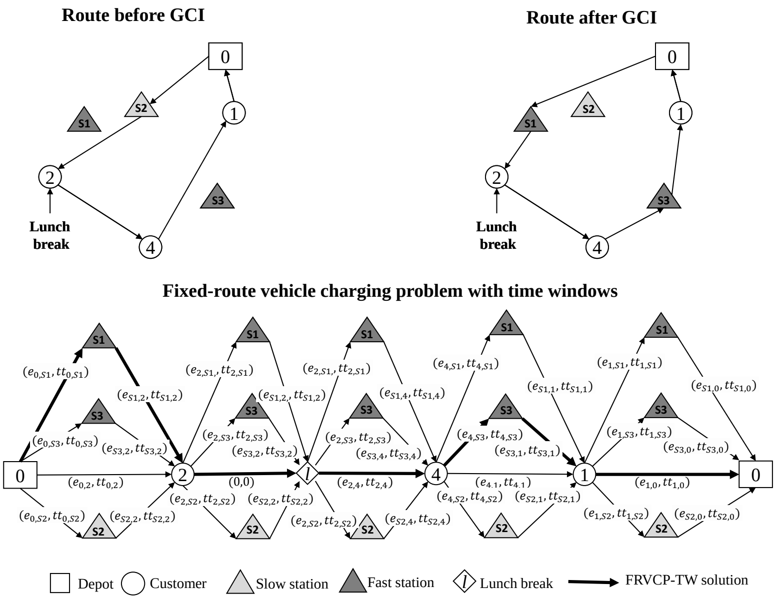

Figure 6: Example of an FRVCP-TW with lunch break for a route with three customers and three available charging stations.

subject to

$$\phi_{\pi(1)} = Q_{vt(p)} - \Big(cf_{tp(p)} \sum_{s \in \mathcal{S}_{vt(p)}} e_{\pi(0)svt(p)} \cdot \varepsilon_{\pi(1)s}\Big) - \Big(cf_{tp(p)} \cdot e_{\pi(0)\pi(1)vt(p)} \cdot (1 - \sum_{s \in \mathcal{S}_{vt(p)}} \varepsilon_{\pi(1)s})\Big) \tag{53}$$

$$\phi_{\pi(i)} = \phi_{\pi(i-1)} - \Big(cf_{tp(p)} \sum_{s \in \mathcal{S}_{vt(p)}} e_{s\pi(i-1)vt(p)} \cdot \varepsilon_{\pi(i-1)s}\Big) - \Big(cf_{tp(p)} \sum_{s \in \mathcal{S}_{vt(p)}} e_{\pi(i-1)svt(p)} \cdot \varepsilon_{\pi(i)s}\Big) + \sum_{s \in \mathcal{S}_{vt(p)}} \gamma_{\pi(i-1)s} - \Big(cf_{tp(p)} \cdot e_{\pi(i-1)\pi(i)vt(p)} \cdot (1 - \sum_{s \in \mathcal{S}_{vt(p)}} \varepsilon_{\pi(i)s})\Big) \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0), \pi(1), \pi(n_r)\} \tag{54}$$

$$\phi_{\pi(n_r)} = \phi_{\pi(n_r-1)} + \sum_{s \in \mathcal{S}_{vt(p)}} \gamma_{\pi(n_r-1)s} + \sum_{s \in \mathcal{S}_{vt(p)}} \gamma_{\pi(n_r)s} - \Big(cf_{tp(p)} \sum_{s \in \mathcal{S}_{vt(p)}} e_{s\pi(n_r-1)vt(p)} \cdot \varepsilon_{\pi(n_r-1)s}\Big) - \Big(cf_{tp(p)} \sum_{s \in \mathcal{S}_{vt(p)}} \Big(e_{\pi(n_r-1)svt(p)} + e_{s\pi(n_r)vt(p)}\Big) \cdot \varepsilon_{\pi(n_r)s}\Big) - \Big(cf_{tp(p)} \cdot e_{\pi(n_r-1)\pi(n_r)vt(p)} \cdot \Big(1 - \sum_{s \in \mathcal{S}_{vt(p)}} \varepsilon_{\pi(n_r)s}\Big)\Big) \tag{55}$$

$$\phi_{\pi(n_r-1)} + \sum_{s \in \mathcal{S}_{vt(p)}} \gamma_{\pi(n_r-1)s} - \Big(cf_{tp(p)} \sum_{s \in \mathcal{S}_{vt(p)}} e_{s\pi(n_r-1)vt(p)} \cdot \varepsilon_{\pi(n_r-1)s}\Big) - \Big(cf_{tp(p)} \sum_{s \in \mathcal{S}_{vt(p)}} e_{\pi(n_r-1)svt(p)} \cdot \varepsilon_{\pi(n_r)s}\Big) \geq 0 \tag{56}$$

$$\phi_{\pi(i)} - Q_{vt(p)} \cdot (1 - \varepsilon_{\pi(i)s}) \leq q_{\pi(i)s} \leq \phi_{\pi(i)} + Q_{vt(p)} \cdot (1 - \varepsilon_{\pi(i)s}) \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, \forall s \in \mathcal{S}_{vt(p)} \tag{57}$$

$$\sum_{b \in B} b \cdot \alpha_{\pi(i)sb} \leq \frac{q_{\pi(i)s}}{Q_{vt(p)}} \cdot 100 \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, \forall s \in \mathcal{S}_{vt(p)} \tag{58}$$

$$\sum_{b \in B} b \cdot \alpha_{\pi(i)sb} \geq \frac{q_{\pi(i)s}}{Q_{vt(p)}} \cdot 100 - 1 \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, s \in \mathcal{S}_{vt(p)} \tag{59}$$

$$o_{\pi(i)s} = q_{\pi(i)s} + \gamma_{\pi(i)s} \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, \forall s \in \mathcal{S}_{vt(p)} \tag{60}$$

$$\sum_{b \in B} b \cdot \rho_{\pi(i)sb} \geq \frac{o_{\pi(i)s}}{Q_{vt(p)}} \cdot 100 \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, \forall s \in \mathcal{S}_{vt(p)} \tag{61}$$

$$\sum_{b \in B} b \cdot \rho_{\pi(i)sb} \leq \frac{o_{\pi(i)s}}{Q_{vt(p)}} \cdot 100 + 1 \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, \forall s \in \mathcal{S}_{vt(p)} \tag{62}$$

$$\sum_{b \in B} \alpha_{\pi(i)sb} \leq \varepsilon_{\pi(i)s} \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, \forall s \in \mathcal{S}_{vt(p)} \tag{63}$$

$$\sum_{b \in B} \rho_{\pi(i)sb} \leq \varepsilon_{\pi(i)s} \quad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, \forall s \in \mathcal{S}_{vt(p)} \tag{64}$$

$$\gamma_{\pi(i)s} \leq Q_{vt(p)} \cdot \varepsilon_{\pi(i)s} \quad \forall \pi(i) \in \overline{\Pi}, \forall s \in \mathcal{S}_{vt(p)} \tag{65}$$

$$\sum \varepsilon_{\pi(i)s} \leq 1 \quad \forall \pi(i) \in \overline{\Pi} \tag{66}$$

$$\left(tt_{\pi(i-1)\pi(i)} \cdot \left(1 - \sum_{s\in\mathcal{S}_{vt(p)}} \varepsilon_{\pi(i)s}\right)\right) + \sum_{s\in\mathcal{S}_{vt(p)}} \delta_{\pi(i)s} \qquad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0)\}, \forall s \in \mathcal{S}_{vt(p)} \quad (68)$$

$$ec_{\pi(i)} \leq \tau_{\pi(i)} \leq lc_{\pi(i)} \qquad \forall \pi(i) \in \overline{\Pi} \setminus \{\pi(0), \pi(n_r)\} \quad (69)$$

$$es_{tp(p)} \leq \tau_{\pi(i)} \leq ls_{tp(p)} \qquad \forall \pi(i) \in \overline{\Pi} \quad (70)$$

$$\gamma_{\pi(i)s} \geq 0, \delta_{\pi(i)s} \geq 0 \qquad \forall \pi(i) \in \overline{\Pi}, \forall s \in \mathcal{S}_{vt(p)} \quad (71)$$

$$\varepsilon_{\pi(i)s} \in \{0,1\} \qquad \forall \pi(i) \in \overline{\Pi}, \forall s \in \mathcal{S}_{vt(p)} \quad (72)$$

$$\phi_{\pi(i)} \geq 0 \qquad \forall \pi(i) \in \overline{\Pi} \quad (73)$$

$$\alpha_{\pi(i)sb} \in \{0,1\}, \rho_{\pi(i)sb} \in \{0,1\}, \qquad \forall \pi(i) \in \overline{\Pi}, \forall s \in \mathcal{S}_{vt(p)}, \forall b \in B \quad (74)$$

$$q_{\pi(i)s} \geq 0, \quad o_{\pi(i)s} \geq 0, \qquad \forall \pi(i) \in \overline{\Pi}, \forall s \in \mathcal{S}_{vt(p)} \quad (75)$$

The objective function (52) minimizes the total cost given by the sum of the travel and charging costs. Constraints (53)–(56) define the SoC when the EV arrives at node $\pi(i) \in \overline{\Pi}$ if $\sum_{s\in\mathcal{S}_{vt(p)}} \varepsilon_{\pi(i)s} = 0$, or to CS $s \in \mathcal{S}_{vt(p)}$ before visiting node $\pi(i) \in \overline{\Pi}$, if $\varepsilon_{\pi(i)s} = 1$. Constraints (57)–(59) define the SoC when the EV arrives at CSs. Constraints (60)–(62) define the SoC when the EV departs from CSs. Constraints (63)–(65) ensure that charging is performed at the visited CSs. Constraints (66) state that at most one CS is visited between any two vertices of the fixed route. Constraints (67) define the time spent charging at CSs. Constraints (68) track the arrival time at each node. Constraints (69) ensure that every node is visited within its TW. Constraints (70) impose the schedule of the technicians of profile $tp(p)$. Finally, constraints (71)–(75) define the domain of the decision variables.

B Detailed computational results

B.1 Detailed results for the E-FSMVRPTW

Tables 5 to 8 show the results of PMa on the small and large E-FSMFTW instances. In Table 5, we compare the PMa results with the heuristic and optimal solutions reported in Hiermann et al. (2016). In Tables 6–8, we compare the PMa results with those of the ALNS of Hiermann et al. (2016) and the HGA of Hiermann et al. (2017). The last rows of the table summarize the average BKS gap, the number of times each method found the BKS, and the average running time. Values in bold indicate that a method found the BKS.

Table 5: Results of PMa on small instances of Hiermann et al. (2016).

Type	A							B							C						
	BnP	ALNS			PMa			BnP	ALNS			PMa			BnP	ALNS			PMa		
Instance	Opt.	Best	Avg.	t (min)	Best	Avg.	t (min)	Opt.	Best	Avg.	t (min)	Best	Avg.	t (min)	Opt.	Best	Avg.	t (min)	Best	Avg.	t (min)
c101c5	857.75	**857.75**	857.75	0.28	**857.75**	857.75	0.03	377.75	**377.75**	377.75	0.23	**377.75**	377.75	0.03	317.75	**317.75**	317.75	0.17	**317.75**	317.75	0.02
c103c5	476.05	**476.05**	476.05	0.21	**476.05**	476.05	0.02	236.05	**236.05**	236.05	0.15	**236.05**	236.05	0.02	206.05	**206.05**	206.05	0.15	**206.05**	206.05	0.02
c206c5	1261.88	**1261.88**	1262.19	0.22	**1261.88**	1261.88	0.02	461.88	**461.88**	461.88	0.16	**461.88**	461.88	0.02	361.88	**361.88**	361.88	0.16	**361.88**	361.88	0.02
c208c5	1164.34	**1164.34**	1164.34	0.18	**1164.34**	1164.34	0.03	364.34	**364.34**	364.34	0.11	**364.34**	364.34	0.02	264.34	**264.34**	264.34	0.15	**264.34**	264.34	0.03
r104c5	327.25	**327.25**	327.25	0.21	**327.25**	327.25	0.03	175.25	**175.25**	175.25	0.12	**175.25**	175.25	0.03	156.25	**156.25**	156.25	0.14	**156.25**	156.25	0.04
r105c5	346.08	**346.08**	346.08	0.19	**346.08**	346.08	0.03	194.08	**194.08**	194.08	0.13	**194.08**	194.08	0.03	175.08	**175.08**	175.08	0.13	**175.08**	175.08	0.03
r202c5	609.18	**609.18**	609.18	0.16	610.54	610.54	0.03	249.18	**249.18**	249.18	0.11	250.54	250.54	0.03	204.18	**204.18**	204.18	0.11	205.54	205.54	0.03
r203c5	645.63	**645.63**	645.63	0.20	**645.63**	645.63	0.03	285.63	**285.63**	285.63	0.11	**285.63**	285.63	0.03	240.63	**240.63**	240.63	0.13	**240.63**	240.63	0.03
rc105c5	511.96	**511.96**	511.96	0.14	**511.96**	511.96	0.04	295.96	**295.96**	295.96	0.15	**295.96**	295.96	0.04	268.96	**268.96**	268.96	0.13	**268.96**	268.96	0.04
rc108c5	532.04	**532.04**	532.04	0.18	**532.04**	532.04	0.03	313.93	**313.93**	313.93	0.17	**313.93**	313.93	0.03	283.93	**283.93**	283.93	0.17	**283.93**	283.93	0.03
rc204c5	496.74	**496.74**	496.74	0.12	498.74	498.74	0.03	255.55	**255.55**	255.79	0.17	258.74	258.74	0.04	220.55	**220.55**	220.86	0.16	228.74	228.74	0.04
rc208c5	328.89	**328.89**	328.89	0.15	**328.89**	328.89	0.03	208.89	**208.89**	208.89	0.14	**208.89**	208.89	0.04	193.89	**193.89**	193.89	0.13	**193.89**	193.89	0.03
c101c10	1302.15	**1302.15**	1302.15	0.24	1308.48	1308.48	0.03	582.15	**582.15**	582.15	0.25	588.48	588.48	0.04	492.15	**492.15**	492.15	0.27	498.48	498.48	0.04
c104c10	902.71	**902.71**	902.71	0.30	**902.71**	902.71	0.03	422.71	**422.71**	422.71	0.31	**422.71**	422.71	0.04	362.71	**362.71**	362.71	0.28	**362.71**	362.71	0.03
c202c10	1304.32	**1304.32**	1493.84	0.25	1312.91	1312.91	0.04	504.32	**504.32**	548.61	0.24	512.91	512.91	0.04	404.32	**404.32**	413.84	0.24	412.91	412.91	0.04
c205c10	2631.97	**2631.97**	2631.97	0.24	2661.17	2661.17	0.05	711.97	**711.97**	711.97	0.24	741.17	741.17	0.05	471.97	**471.97**	471.97	0.17	501.17	501.17	0.05
r102c10	595.34	**595.34**	595.34	0.23	**595.34**	595.34	0.07	325.19	**325.19**	325.19	0.24	**325.19**	325.19	0.07	287.19	**287.19**	287.19	0.20	**287.19**	287.19	0.07
r103c10	478.07	**478.07**	478.23	0.24	**478.07**	483.59	0.08	262.07	**262.07**	262.07	0.29	**262.07**	262.07	0.07	235.07	**235.07**	235.07	0.34	**235.07**	235.07	0.08
r201c10	1138.38	**1138.38**	1140.45	0.27	**1138.38**	1138.38	0.05	418.38	**418.38**	418.38	0.28	**418.38**	418.38	0.05	328.38	**328.38**	328.38	0.29	**328.38**	328.38	0.05
r203c10	952.16	**952.16**	956.50	0.23	956.59	956.59	0.06	392.16	**392.16**	438.29	0.23	396.59	396.59	0.06	322.16	**322.16**	350.29	0.22	326.59	326.59	0.06
rc102c10	1100.27	**1100.27**	1100.27	0.27	**1100.27**	1100.27	0.03	572.27	**572.27**	572.27	0.23	**572.27**	572.27	0.04	498.51	**498.51**	498.51	0.22	**498.51**	498.51	0.04
rc108c10	693.27	**693.27**	693.27	0.35	**693.27**	693.27	0.03	422.12	**422.12**	422.12	0.26	424.09	424.09	0.04	386.12	**386.12**	386.12	0.25	388.09	388.09	0.03
rc201c10	684.63	**684.63**	684.88	0.30	686.32	686.32	0.07	429.17	**429.17**	429.17	0.45	434.83	434.83	0.06	384.17	**384.17**	384.17	0.32	389.83	389.83	0.06
rc205c10	1064.59	**1064.59**	1067.44	0.29	1066.14	1066.14	0.07	504.59	**504.59**	504.59	0.38	506.14	506.14	0.07	429.69	**429.69**	429.69	0.27	**429.69**	429.69	0.07
c103c15	1291.03	**1291.03**	1291.46	0.50	**1291.03**	1291.03	0.09	571.03	**571.03**	571.78	0.55	**571.03**	571.03	0.09	481.03	**481.03**	481.64	0.43	**481.03**	481.03	0.09
c106c15	1253.59	**1253.59**	1253.59	0.49	**1253.59**	1253.59	0.08	533.59	**533.59**	538.28	0.55	**533.59**	533.59	0.08	415.13	**415.13**	440.52	0.48	**415.13**	415.13	0.08
c202c15	2403.35	**2403.35**	2403.35	0.64	**2403.35**	2403.35	0.10	803.35	**803.35**	803.35	0.61	**803.35**	803.35	0.10	603.35	**603.35**	607.82	0.61	**603.35**	603.35	0.10
c208c15	2325.89	**2325.89**	2325.89	0.53	**2325.89**	2325.89	0.12	725.89	**725.89**	725.89	0.47	**725.89**	725.89	0.10	525.89	**525.89**	526.29	0.38	**525.89**	525.89	0.11
r102c15	850.58	**850.58**	854.99	0.50	**850.58**	850.58	0.09	511.55	**511.55**	514.84	0.56	**511.55**	511.55	0.09	465.94	**465.94**	467.00	0.51	466.55	466.55	0.09
r105c15	760.13	**760.13**	762.48	0.41	**760.13**	760.13	0.10	436.89	**436.89**	436.89	0.43	**436.89**	436.89	0.10	387.89	**387.89**	387.94	0.38	**387.89**	387.89	0.10
r202c15	1311.24	**1311.24**	1316.84	0.92	**1311.24**	1311.24	0.13	591.24	**591.24**	591.24	0.74	**591.24**	591.24	0.13	495.64	**495.64**	495.64	0.55	498.05	498.05	0.12
r209c15	1033.50	**1033.50**	1033.50	0.64	**1033.50**	1033.50	0.12	473.50	**473.50**	473.50	0.63	**473.50**	473.50	0.12	403.50	**403.50**	403.50	0.55	**403.50**	403.50	0.12
rc103c15	840.97	**840.97**	840.98	0.52	**840.97**	842.90	0.08	499.67	**499.67**	499.67	0.43	**499.67**	499.67	0.07	448.67	**448.67**	448.67	0.43	**448.67**	448.67	0.08
rc108c15	1013.70	**1013.70**	1033.14	0.47	**1013.70**	1013.70	0.09	514.78	**514.78**	514.78	0.44	**514.78**	514.78	0.09	445.25	**445.25**	445.95	0.41	**445.25**	445.25	0.09
rc202c15	1101.61	**1101.61**	1101.61	0.56	**1101.61**	1101.61	0.14	541.61	**541.61**	541.61	0.51	**541.61**	541.61	0.14	471.61	**471.61**	471.61	0.44	**471.61**	471.61	0.14
rc204c15	810.90	**810.90**	810.90	0.54	**810.90**	810.90	0.23	410.90	**410.90**	410.90	0.59	**410.90**	410.90	0.23	360.90	**360.90**	360.90	0.52	**360.90**	360.90	0.22
Avg. gap (%)		0.00	0.52		0.10	0.14			0.00	0.62		0.33	0.33			0.00	0.52		0.50	0.50	
Best		36			28				36			27				36			26		
Avg. Time				0.34			0.07				0.32			0.06				0.29			0.06

Table 6: Results of PMa on large instances of Hiermann et al. (2016), Type A

Type A		ALNS			HGA			PMa		
Instance	BKS	Best	Avg.	t (min)	Best	Avg.	t (min)	Best	Avg.	t (min)
c101	7160.77	7180.42	7190.21	17.53	**7160.77**	7162.29	21.12	7162.01	7164.33	16.05
c102	7137.04	7154.50	7162.24	17.95	**7137.04**	7141.25	21.86	7139.65	7142.73	16.24
c103	7117.32	7126.29	7149.31	18.30	**7117.32**	7122.27	22.93	7120.27	7122.85	17.49
c104	7097.80	7100.22	7110.43	17.75	**7097.80**	7098.38	23.99	7099.88	7101.63	17.96
c105	7138.85	7155.23	7182.56	17.60	**7138.85**	7156.31	21.15	7141.53	7146.79	16.50
c106	7134.75	7146.88	7168.94	17.69	**7134.75**	7140.15	21.92	7137.65	7140.61	16.51
c107	7136.44	7156.18	7171.04	17.42	**7136.44**	7142.77	21.24	7138.49	7143.14	17.17
c108	7131.83	7141.49	7153.77	17.53	**7131.83**	7139.50	21.99	7133.30	7136.92	17.21
c109	7113.94	7120.33	7132.19	17.32	**7113.94**	7120.07	22.39	7123.07	7129.63	17.90
c201	5736.11	5737.57	5757.53	39.28	**5736.11**	5738.23	13.72	5737.57	5740.41	18.35
c202	5733.53	5744.65	5765.52	42.22	**5733.53**	5735.61	15.76	5738.95	5745.45	20.31
c203	5713.38	5726.08	5751.99	47.69	**5713.38**	5713.38	18.73	5719.31	5727.83	22.67
c204	5689.04	5705.82	5727.18	50.91	**5689.04**	5691.37	21.21	5703.78	5713.80	25.79
c205	5693.45	5703.48	5725.41	46.16	**5693.45**	5696.48	15.21	5694.58	5703.65	19.90
c206	5687.96	5708.77	5714.39	31.20	**5687.96**	5687.96	16.90	5689.08	5700.21	21.34
c207	5693.23	5697.99	5713.44	32.58	**5693.23**	5694.47	17.30	5694.88	5705.81	21.62
c208	5681.47	5685.40	5707.65	50.23	**5681.47**	5681.47	16.10	5682.60	5688.60	22.39
r101	4366.21	4426.85	4465.51	14.47	4372.29	4382.32	9.12	**4366.21**	4371.45	7.58
r102	4174.55	4245.82	4270.92	14.97	4186.74	4202.05	10.06	**4174.55**	4176.27	6.20
r103	4042.90	4103.35	4130.86	16.43	4048.37	4060.29	11.82	**4042.90**	4045.58	11.62
r104	3963.57	4007.28	4025.60	15.27	3966.74	3972.91	13.77	**3963.57**	3965.33	16.67
r105	4132.55	4181.80	4215.34	15.37	4145.27	4154.04	9.51	**4132.55**	4133.58	5.63
r106	4072.06	4120.23	4155.24	15.54	4078.17	4087.59	11.22	**4072.06**	4072.06	13.15
r107	4000.31	4057.06	4093.59	15.30	4000.69	4011.87	12.26	**4000.31**	4005.75	18.05
r108	3948.81	3992.57	4025.75	15.77	3961.92	3968.72	17.29	**3948.81**	3953.83	15.83
r109	4014.85	4067.14	4110.98	15.58	4023.64	4034.36	11.85	**4014.85**	4017.32	9.57
r110	3968.51	4024.71	4045.96	15.73	3973.72	3991.65	16.88	**3968.51**	3968.51	18.33
r111	3969.91	4023.38	4048.42	15.93	3984.77	3990.36	16.66	**3969.91**	3973.20	18.05
r112	3937.80	4001.87	4023.01	15.80	3942.66	3955.19	16.23	**3937.80**	3940.40	13.58
r201	3399.82	3413.93	3432.83	42.20	**3399.82**	3410.53	17.61	3510.07	3528.62	8.69
r202	3266.47	3270.49	3295.26	44.95	**3266.47**	3275.73	20.93	3341.76	3358.85	9.37
r203	3127.56	3136.47	3169.97	49.40	**3127.56**	3137.34	24.10	3196.99	3212.43	11.58
r204	3002.72	3008.01	3026.09	46.32	**3002.72**	3003.15	29.11	3065.71	3081.30	15.07
r205	3230.20	3234.26	3261.16	40.89	**3230.20**	3240.34	20.48	3317.45	3330.88	9.98
r206	3156.58	3172.50	3194.12	47.73	**3156.58**	3161.18	22.96	3248.15	3260.98	13.27
r207	3059.85	3079.39	3099.52	46.87	**3059.85**	3062.33	28.94	3127.43	3145.30	12.55
r208	2995.96	3010.51	3026.57	51.26	**2995.96**	2999.40	34.17	3053.61	3062.66	15.40
r209	3122.41	3142.72	3161.57	45.06	**3122.41**	3133.33	23.40	3196.65	3210.85	10.82
r210	3101.10	3110.90	3143.79	45.94	**3101.10**	3109.03	22.95	3167.78	3183.95	12.06
r211	3026.74	3041.93	3079.24	44.29	**3026.74**	3030.99	28.18	3093.66	3115.15	13.48
rc101	5250.72	5294.01	5346.49	14.13	5254.50	5261.36	9.06	**5250.72**	5252.98	6.62
rc102	5069.43	5121.53	5180.03	14.63	**5069.43**	5096.49	10.34	5099.78	5112.36	15.26
rc103	4897.58	4958.51	5007.37	14.53	4905.29	4929.17	9.41	**4897.58**	4906.22	13.83
rc104	4783.16	4804.00	4862.65	16.03	**4783.16**	4808.85	10.50	4789.16	4796.11	14.15
rc105	5044.93	5074.43	5117.09	14.48	**5044.93**	5063.17	9.95	5053.55	5056.93	10.22
rc106	4981.50	5028.28	5102.46	14.69	4991.29	5002.07	9.97	**4981.50**	4990.91	7.93
rc107	4836.81	4864.78	4913.90	15.24	**4836.81**	4859.83	10.66	4838.06	4846.06	12.10
rc108	4778.64	4814.33	4862.41	15.64	4800.17	4815.83	10.25	**4778.64**	4794.01	13.18
rc201	4337.60	4346.25	4361.17	14.27	**4337.60**	4343.47	21.58	4353.79	4368.88	20.88
rc202	4267.75	4273.74	4295.27	14.59	**4267.75**	4271.96	24.23	4279.09	4294.44	19.13
rc203	4147.68	4152.94	4186.28	15.98	**4147.68**	4152.79	26.63	4162.99	4176.54	22.14
rc204	4094.11	4113.49	4127.11	19.18	**4094.11**	4096.59	29.46	4098.58	4110.39	26.73
rc205	4242.63	4246.52	4273.59	14.86	**4242.63**	4248.30	23.58	4252.31	4273.58	21.30
rc206	4236.43	4237.75	4270.25	15.09	**4236.43**	4241.71	24.08	4247.68	4264.89	20.66
rc207	4169.59	4177.23	4199.60	16.20	**4169.59**	4174.39	26.14	4192.66	4199.96	21.78
rc208	4096.01	4097.04	4122.12	18.13	**4096.01**	4103.79	30.99	4109.01	4122.11	25.06
Avg. Gap (%)		0.56	1.19		0.06	0.24		0.55	0.76	
Best		0			40			16		
Avg. Time				25.68			18.75			15.77

Table 7: Results of PMa on large instances of Hiermann et al. (2016), Type B

Type B		ALNS			HGA			PMa		
Instance	BKS	Best	Avg.	t (min)	Best	Avg.	t (min)	Best	Avg.	t (min)
c101	2495.00	**2495.00**	2505.73	14.43	**2495.00**	2496.28	13.59	2496.02	2496.97	15.99
c102	2445.99	**2445.99**	2450.73	14.41	**2445.99**	2446.48	13.85	2448.76	2449.23	16.15
c103	2427.44	2438.54	2452.40	15.03	**2427.44**	2435.42	19.49	2436.07	2443.86	17.44
c104	2402.47	2404.97	2428.95	15.07	**2402.47**	2404.40	20.12	2405.25	2408.51	17.91
c105	2472.60	2472.93	2475.95	14.45	**2472.60**	2473.14	17.21	**2472.60**	2475.59	16.39
c106	2456.74	2462.54	2468.13	14.71	**2456.74**	2459.90	16.63	2459.16	2463.88	16.46
c107	2457.89	2458.37	2461.32	14.60	**2457.89**	2457.98	16.53	**2457.89**	2458.08	17.06
c108	2448.08	2450.17	2463.02	14.33	**2448.08**	2451.13	18.82	2448.58	2453.25	17.11
c109	2430.58	2436.41	2452.57	15.07	2431.36	2432.77	19.22	2431.17	2437.87	17.84
c201	1730.41	**1730.41**	1739.26	35.76	**1730.41**	1730.41	14.51	**1730.41**	1730.41	7.71
c202	1729.73	1737.57	1745.24	38.14	**1729.73**	1730.05	16.40	**1729.73**	1729.99	8.09
c203	1713.38	1716.29	1742.76	39.38	**1713.38**	1713.38	18.46	1719.31	1723.66	10.34
c204	1689.04	1699.07	1709.43	37.02	**1689.04**	1690.01	21.42	1703.20	1706.75	15.70
c205	1693.45	1697.01	1715.09	37.83	**1693.45**	1694.83	15.38	1694.58	1695.10	7.69
c206	1687.96	1693.15	1712.38	36.78	**1687.96**	1687.96	16.68	1689.08	1694.06	9.88
c207	1693.23	1694.61	1710.70	35.05	**1693.23**	1694.47	16.92	1694.36	1696.40	10.70
c208	1681.47	**1681.47**	1707.11	36.46	**1681.47**	1681.47	16.56	1682.60	1684.91	10.42
r101	2249.14	2261.21	2281.28	13.68	**2249.24**	2258.24	7.75	2253.04	2253.33	4.26
r102	2047.89	2073.03	2095.87	14.45	**2047.89**	2063.58	8.80	2049.99	2051.42	3.63
r103	1886.27	1894.98	1927.52	15.11	1898.26	1906.46	9.50	1887.13	1891.20	6.40
r104	1745.75	1747.65	1775.33	15.28	1754.22	1766.32	10.63	**1745.75**	1752.01	16.65
r105	1997.75	2010.31	2030.12	15.08	2007.40	2013.63	8.79	2002.59	2004.68	4.08
r106	1921.42	1934.00	1963.88	14.51	1925.56	1948.02	9.52	1922.12	1925.28	6.17
r107	1809.54	1824.88	1844.20	15.50	1824.68	1842.49	10.21	1811.88	1813.81	17.51
r108	1712.40	1729.18	1753.09	16.27	**1712.40**	1732.21	10.93	1717.11	1721.70	16.15
r109	1852.35	1871.54	1904.12	15.37	1861.15	1877.84	9.75	**1852.35**	1856.96	11.91
r110	1747.70	1759.69	1793.48	15.54	1766.10	1786.94	10.67	**1747.70**	1750.49	8.87
r111	1761.26	1786.97	1808.36	15.66	1769.41	1793.86	10.62	**1761.26**	1766.75	15.65
r112	1694.66	1721.79	1746.02	15.77	1705.89	1717.98	10.74	**1694.66**	1704.38	13.69
r201	1591.35	1594.58	1618.25	31.21	**1591.35**	1597.16	14.57	1729.91	1739.18	10.41
r202	1461.63	1468.05	1479.42	29.61	**1461.63**	1468.59	18.31	1541.76	1565.02	8.45
r203	1327.56	1340.00	1354.24	30.70	**1327.56**	1334.67	20.54	1396.99	1412.43	10.62
r204	1202.72	1203.89	1211.63	27.35	**1202.72**	1205.19	26.38	1265.71	1280.87	13.04
r205	1429.32	1430.70	1455.08	30.16	**1429.32**	1433.53	17.53	1517.45	1530.88	9.13
r206	1355.90	1361.69	1376.34	31.35	**1355.90**	1357.28	19.56	1448.15	1464.26	12.19
r207	1256.22	**1256.22**	1268.66	28.18	1257.88	1260.31	24.61	1327.43	1345.30	11.21
r208	1195.96	1198.39	1208.89	29.02	**1195.96**	1198.80	28.35	1253.61	1262.66	14.33
r209	1321.76	1333.33	1345.50	30.30	**1321.76**	1329.72	20.01	1396.65	1411.24	10.63
r210	1298.78	1314.16	1324.07	30.07	**1298.78**	1301.00	19.12	1367.78	1387.56	10.63
r211	1226.74	1231.38	1244.73	26.30	**1226.74**	1233.22	23.49	1293.66	1320.07	12.37
rc101	2499.98	2548.84	2560.33	13.71	2501.78	2514.33	8.63	**2499.98**	2503.77	3.83
rc102	2315.01	2330.50	2359.92	14.35	**2315.01**	2326.17	9.07	2326.25	2330.96	4.11
rc103	2104.93	2105.84	2136.78	14.14	2116.31	2126.76	9.79	**2104.93**	2108.43	4.41
rc104	1973.51	1986.35	2002.33	15.56	1973.78	1980.44	10.48	1975.71	1979.18	7.06
rc105	2248.20	2259.97	2287.95	13.87	2250.37	2259.34	9.18	2251.25	2256.57	3.96
rc106	2185.50	2209.73	2232.05	14.50	2194.61	2213.35	9.71	2187.30	2188.30	4.07
rc107	2012.53	2037.25	2050.20	15.43	**2012.53**	2043.64	9.69	2026.09	2030.95	7.28
rc108	1962.87	**1962.87**	1995.41	14.99	1967.99	1974.87	9.98	1969.64	1971.36	8.44
rc201	1899.99	**1899.99**	1931.42	15.69	**1899.99**	1912.42	10.71	1953.90	1966.34	8.26
rc202	1805.24	1807.30	1825.07	16.19	**1805.24**	1807.50	14.68	1847.98	1863.52	10.82
rc203	1637.32	1642.43	1660.93	19.00	**1637.32**	1649.11	15.48	1658.04	1678.16	9.86
rc204	1520.59	1521.80	1543.04	22.13	**1520.59**	1526.04	19.91	1533.09	1545.23	14.09
rc205	1747.39	1753.79	1774.22	19.03	**1747.39**	1758.96	13.08	1811.93	1825.84	15.25
rc206	1742.98	1751.75	1767.75	17.79	**1742.98**	1757.36	13.91	1790.46	1807.41	14.13
rc207	1603.23	1616.96	1640.23	19.07	**1603.23**	1611.17	15.34	1674.53	1679.85	12.78
rc208	1495.34	1497.95	1520.76	22.03	**1495.34**	1499.75	21.06	1510.60	1537.60	13.47
Avg. Gap (%)		0.48	1.52		0.12	0.55		1.59	2.07	
Best		7			39			11		
Avg. Time				21.47			15.05			11.12

Table 8: Results of PMa on large instances of Hiermann et al. (2016), Type C

Type C		ALNS			HGA			PMa		
Instance	BKS	Best	Avg.	t (min)	Best	Avg.	t (min)	Best	Avg.	t (min)
c101	1809.93	1810.12	1816.06	14.08	**1809.93**	1809.97	7.06	1811.15	1813.32	2.64
c102	1759.73	**1759.73**	1766.14	14.36	**1759.73**	1759.73	7.91	1762.50	1767.80	3.03
c103	1744.92	1755.02	1759.20	15.09	**1744.92**	1745.33	11.06	**1744.92**	1750.74	8.60
c104	1717.33	1719.67	1735.86	15.60	**1717.33**	1718.73	10.10	1721.57	1722.18	13.77
c105	1783.25	**1783.25**	1785.43	14.51	**1783.25**	1783.92	7.19	1784.48	1785.57	3.17
c106	1772.74	1774.77	1777.67	14.64	**1772.74**	1773.57	8.09	1775.08	1776.92	3.54
c107	1764.02	**1764.02**	1768.33	14.57	**1764.02**	1765.09	7.90	1764.25	1767.63	4.29
c108	1760.63	1761.41	1769.76	14.80	**1760.63**	1762.95	8.79	1760.86	1765.29	7.44
c109	1738.93	1740.18	1749.07	15.30	**1738.93**	1740.78	9.17	1741.89	1743.78	15.56
c201	1210.41	**1210.41**	1213.63	31.30	**1210.41**	1210.41	13.84	**1210.41**	1210.41	5.04
c202	1209.73	**1209.73**	1220.97	34.17	**1209.73**	1209.86	15.72	**1209.73**	1209.90	6.86
c203	1207.95	1212.34	1227.69	33.07	**1207.95**	1208.22	17.96	1208.74	1209.02	8.48
c204	1175.94	1179.25	1199.37	32.15	**1175.94**	1177.50	20.00	1183.20	1189.03	12.38
c205	1188.92	**1188.92**	1195.24	31.64	**1188.92**	1192.69	15.94	1192.54	1193.18	6.50
c206	1183.42	**1183.42**	1192.30	31.01	**1183.42**	1183.42	17.40	1188.81	1188.81	7.98
c207	1183.42	**1183.42**	1190.37	31.44	**1183.42**	1183.42	17.17	1187.49	1187.49	8.19
c208	1181.47	**1181.47**	1192.96	30.82	**1181.47**	1181.47	16.70	1182.60	1187.13	8.94
r101	1954.00	1961.02	1977.89	14.36	1954.56	1957.89	7.82	1959.04	1959.07	3.92
r102	1757.13	1765.36	1791.03	14.67	1757.91	1760.92	8.64	1761.48	1763.72	3.42
r103	1584.58	1601.23	1618.81	15.52	1589.17	1603.05	9.65	1586.58	1587.07	5.12
r104	1417.69	1424.30	1448.31	16.20	**1417.69**	1435.56	10.97	1423.54	1428.86	12.56
r105	1699.34	1704.36	1728.12	14.68	1708.92	1714.26	9.10	1704.17	1706.48	3.86
r106	1603.24	1611.62	1635.42	14.67	**1603.24**	1623.31	9.55	1607.71	1610.13	4.03
r107	1482.74	1490.04	1514.01	15.99	1493.27	1500.84	10.27	1487.70	1490.47	11.43
r108	1386.74	1399.27	1417.39	16.42	1389.46	1399.22	10.58	1388.59	1392.37	9.64
r109	1546.83	1560.34	1580.14	15.65	1552.48	1566.61	10.03	1547.48	1549.52	10.48
r110	1419.27	1446.48	1471.66	15.64	1434.84	1447.59	10.43	**1419.27**	1422.42	5.25
r111	1434.87	1457.68	1479.75	16.16	1441.99	1460.14	10.53	**1434.87**	1436.55	5.61
r112	1379.95	1389.87	1403.82	16.10	1385.84	1398.31	10.98	1380.66	1386.53	16.90
r201	1366.63	**1366.63**	1378.77	29.69	1368.94	1378.37	13.30	1495.06	1502.75	12.49
r202	1236.97	**1236.97**	1249.65	29.13	1245.49	1249.56	17.10	1335.25	1351.33	13.40
r203	1102.56	1104.85	1124.07	30.23	**1102.56**	1107.65	19.49	1172.27	1190.38	13.02
r204	977.72	**977.72**	983.97	26.81	**977.72**	978.93	24.84	1033.28	1041.05	11.62
r205	1197.20	1217.77	1232.63	29.15	**1197.20**	1205.62	17.35	1292.45	1304.49	9.66
r206	1130.90	1136.83	1155.47	30.95	**1130.90**	1133.39	18.26	1223.15	1238.63	13.19
r207	1031.22	**1031.22**	1057.22	26.31	**1031.22**	1033.95	23.80	1102.43	1119.45	12.30
r208	970.96	971.15	984.87	28.21	**970.96**	973.34	28.08	1031.22	1038.18	18.31
r209	1092.26	1099.24	1117.68	29.62	**1092.26**	1100.36	18.11	1171.65	1185.83	11.85
r210	1069.71	1087.21	1100.27	29.88	**1069.71**	1077.86	18.35	1142.78	1153.78	11.55
r211	1001.74	1006.38	1026.07	25.93	**1001.74**	1005.16	22.23	1068.66	1093.57	15.19
rc101	2116.92	2142.24	2153.24	13.80	2119.70	2134.84	8.96	2120.77	2120.99	3.66
rc102	1945.31	1957.11	1972.85	14.68	**1945.31**	1959.96	9.60	1946.22	1948.38	3.67
rc103	1725.73	1736.25	1764.22	14.54	1733.70	1745.83	10.03	1726.34	1727.08	4.00
rc104	1584.79	1595.44	1614.09	15.80	**1584.79**	1596.48	10.40	1592.48	1600.62	6.59
rc105	1870.80	1885.63	1900.42	14.14	**1870.80**	1881.65	9.67	1873.75	1877.12	3.83
rc106	1808.96	1823.89	1844.99	15.18	**1808.96**	1814.28	9.90	1811.86	1812.94	4.00
rc107	1635.51	1639.84	1675.58	15.31	**1635.51**	1656.95	10.19	1643.52	1646.70	4.83
rc108	1578.51	**1578.51**	1601.47	14.98	1583.08	1586.20	10.91	1583.70	1585.13	6.03
rc201	1588.25	1589.99	1617.52	15.64	**1588.25**	1598.69	11.07	1626.41	1642.50	6.68
rc202	1481.05	1485.13	1497.99	16.72	**1481.05**	1483.05	15.40	1523.43	1533.44	6.39
rc203	1310.37	**1310.37**	1333.25	19.35	1310.48	1316.19	16.57	1333.75	1347.73	8.54
rc204	1182.32	1183.16	1193.93	22.69	**1182.32**	1186.42	21.22	1193.09	1204.59	13.10
rc205	1422.39	1424.75	1440.00	20.95	**1422.39**	1426.02	14.55	1480.90	1491.38	9.91
rc206	1429.47	1431.21	1439.17	18.11	**1429.47**	1434.12	14.54	1474.83	1480.37	10.18
rc207	1273.23	1277.71	1299.14	21.30	**1273.23**	1280.53	15.47	1328.24	1337.71	9.22
rc208	1159.70	1161.57	1171.52	22.91	**1159.70**	1163.21	22.02	1175.60	1195.11	11.47
Avg. Gap (%)		0.41	1.51		0.11	0.52		1.91	2.39	
Best		15			40			5		
Avg. Time				20.83			13.61			8.45

B.2 Results for TRSP-CEV instances

Table 9 shows the PMa results for the small TRSP-CEV instances with five and ten customers. The naming convention (TRSP-CEV-n-id) indicates the number of customers n and the instance id. For example, TRSP-CEV5-1 refers to the first instance with five customers. We compare our results with the optimal solutions found by Gurobi using the MILP formulation presented in Section 3.1 with $\beta = 2$. For the PMa results, we report the best solution, the average solution (Avg.), and the average computing time (t in seconds) over ten runs. The last rows of the table summarize the average gap, the number of times PMa found the optimal solution, and the average running time.

Table 9: Results of PMa on small instances of TRSP-CEV

	Gurobi		**PMa**		
Instance	**Opt.**	**t(s)**	**Best**	**Avg.**	**t(s)**
TRSP-CEV5-1	805.30	2.11	805.30	805.30	0.01
TRSP-CEV5-2	806.31	6.56	806.31	806.31	0.02
TRSP-CEV5-3	801.26	6.83	801.26	801.26	0.03
TRSP-CEV5-4	802.52	5.07	802.51	802.51	0.00
TRSP-CEV5-5	801.63	909.41	801.63	801.63	0.02
TRSP-CEV10-1	810.14	2367.25	810.14	810.14	1.90
TRSP-CEV10-2	1625.13	56012.63	1625.13	1625.13	3.33
TRSP-CEV10-3	807.61	1563.10	807.61	807.61	1.87
TRSP-CEV10-4	802.10	4589.40	802.10	802.10	0.03
TRSP-CEV10-5	803.01	8107.00	803.01	803.01	0.04
Avg. Gap (%)			0.00	0.00	
Number of optimal solutions			10		
Avg. Time		7356.94			0.73

Table 10 shows the PMa results for the large TRSP-CEV instances. For each instance and EV percentage, we report (i) the best solution, (ii) the average cost (Avg.), and (iii) the average computing time (t in minutes). The averages are computed over 10 runs. The last rows of the table summarize the average gap and the average running time. The value NF indicates that no feasible solution was found.

Table 10: Results of PMa on large instances of TRSP-CEV

% of EVs	**0%**			**20%**			**40%**			**60%**			**80%**			**100%**		
Instance	**Best**	**Avg.**	**t(min)**	**Best**	**Avg.**	**t(min)**	**Best**	**Avg.**	**t(min)**	**Best**	**Avg.**	**t(min)**	**Best**	**Avg.**	**t(min)**	**Best**	**Avg.**	**t(min)**
urban_18	4146.03	4151.83	15.65	4075.87	4084.71	15.62	4011.38	4012.24	15.65	4011.08	4012.06	15.65	4010.89	4011.79	15.64	4010.21	4011.29	15.66
urban_19	4896.89	4902.50	18.72	4860.62	4864.56	18.85	4818.00	4823.99	18.74	4813.67	4815.30	18.81	4813.60	4815.08	18.71	4813.16	4814.15	18.74
urban_21	3326.54	3342.79	14.83	3250.57	3259.42	14.82	3210.32	3210.99	14.86	3209.13	3210.66	14.92	3209.13	3210.45	14.83	3209.13	3210.26	14.83
urban_22	4143.85	4154.02	17.58	4079.63	4091.19	17.57	4011.78	4015.26	17.56	4011.09	4012.22	17.55	4011.22	4012.14	17.58	4010.38	4011.77	17.55
semi_urban_18	4360.36	4369.74	26.41	4153.46	4166.51	26.51	4025.11	4026.49	26.38	4022.85	4025.56	26.50	4023.76	4025.32	26.47	4022.70	4025.23	26.65
semi_urban_19	3395.10	3400.19	18.36	3274.29	3282.86	18.34	3212.98	3213.42	18.35	3212.41	3212.77	18.33	3212.20	3212.64	18.35	3212.11	3212.50	18.59
semi_urban_20	7631.26	7651.25	36.93	7485.31	7509.84	36.73	7338.37	7353.63	36.67	7267.54	7296.12	36.19	7233.04	7235.45	36.39	7231.59	7234.64	36.60
semi_urban_21	6849.46	6878.22	31.83	6639.11	6665.28	31.96	6510.51	6555.98	30.99	6452.27	6461.16	31.46	6437.38	6452.86	31.10	6439.42	6449.42	31.79
semi_urban_22	6056.08	6073.94	32.09	5854.48	5872.35	31.94	5679.32	5685.31	30.84	5632.04	5634.27	32.10	5633.62	5634.04	32.45	5630.98	5632.55	31.27
rural_18	7297.66	7303.59	19.39	7089.58	7107.61	19.39	6948.50	6953.87	19.38	6924.40	6929.84	19.36	6900.19	6904.27	19.39	NF	NF	NF
rural_19	4557.25	4557.78	16.20	4327.21	4336.61	16.15	4242.39	4246.90	16.15	4252.06	4254.65	16.17	4252.06	4254.13	16.36	NF	NF	NF
rural_20	6530.05	6530.41	14.43	6325.86	6326.84	15.81	6089.57	6190.33	21.63	6044.53	6047.70	21.92	6020.81	6036.80	17.73	NF	NF	NF
rural_21	8551.71	8590.10	21.12	NF	NF	NF	NF	NF	NF	NF	NF	NF	NF	NF	NF	NF	NF	NF
rural_22	6571.22	6599.66	18.22	6331.74	6350.65	18.25	6124.44	6159.62	18.06	6025.45	6029.21	18.11	5859.00	5860.30	18.08	NF	NF	NF
Avg. Gap (%)		0.24			0.25			0.29			0.08			0.07			0.05	
Avg. Time (min)			21.55			21.69			21.94			22.08			21.78			23.52

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