The green mixed fleet vehicle routing problem with partial battery recharging and time windows

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Abstract

This work presents a new variant of the Green Vehicle Routing Problem with time windows. We propose an iterative local search heuristic to optimize the routing of a mixed vehicle fleet, composed of electric and conventional (internal combustion engine) vehicles. Since the batteries of electric vehicles have a limited autonomy of the battery, we consider the possibility of recharging partially at any of the available stations. In addition, we explicitly take into account a limitation on the polluting emissions for the conventional vehicles. The behaviour of the proposed approach is evaluated empirically on a large set of test instances.

Keywords: green vehicle routing; mixed fleet; electric vehicles; pollution routing; iterated local search.

1 Introduction

In recent years, we have witnessed a growing interest in environmental problems related to polluting emissions, noise and congestion in the transport industry. In this context, developing environmentally friendly and efficient transport and distribution systems represents an important challenge. As a result, several researchers have begun analysing and studying classical vehicle routing problems (VRPs) from a green perspective, by incorporating sustainability goals with a primary focus on the reduction of environmental externalities. We refer to these problems as Green-VRPs (G-VRPs). The aim of this paper is to present a new G-VRP model in which a mixed fleet of electric and conventional vehicles is considered and which explicitly takes into account the polluting emissions. We develop an

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efficient heuristic for the proposed problem. In the following, we review the literature related to the G-VRPs variants concerning sustainable transport issues.

1.1 Literature review on the G-VRPs with conventional vehicles

In order to reduce negative externalities, routing models and procedures have to consider sustainable factors and offer new transport strategies and solutions. One possible approach is to minimize the polluting emissions by including the emission costs into the objective function. Figliozzi [10] presented a time-dependent VRP with time windows (T-DVRP). The author calculated the amount of fuel spent with the purpose of studying the impacts of congestion, land use and travel speed on CO_2 emissions. Bektaş and Laporte [1] modeled for the first time the energy consumption of conventional vehicles and explicitly considered the polluting emissions impact. They called this problem the Pollution-Routing Problem (PRP), and presented a non-linear mixed integer mathematical problem for it. This paper lead to several modeling and algorithmic extensions. Thus Demir et al. [4] highlighted the difficulty of solving medium-scale PRPs by using the model presented in Bektaş and Laporte [1]. After introducing an extended PRP, they proposed an effective adaptive large neighborhood search (ALNS) heuristic capable of solving instances with up to 200 nodes. Since CO_2 emissions are directly related to vehicle speed, Jabali et al. [15] solved a T-DVRP by tabu search, considering maximum achievable vehicle speed as part of the optimization. These authors considered a two-stage planning horizon: free traffic flow and congestion. They modeled and minimized the emissions per kilometer as a function of speed, and highlighted the relationship between reducing emissions and routing cost. Since the minimization of fuel consumption and driving time are conflicting, Demir et al. [5] introduced and solved the bi-objective PRP, in which they jointly minimized the two conflicting factors. Franceschetti et al. [11] considered the Time-Dependent PRP with time windows, an extension of the PRP that explicitly takes into account traffic congestion. Tajik et al. [35] introduced uncertain data in the Time-Dependent PRP with pickup and delivery. They defined a mixed integer linear program in which the main objective is to minimize the traveled distance, the number of vehicles and the polluting emissions. They then introduced a robust counterpart, considering vehicle speed as an uncertain parameter. Koç et al. [17] introduced a heterogeneous fleet in the PRP, called the fleet size and mix pollution-routing problem, and demonstrated the benefit of using a heterogeneous fleet over a homogeneous one. Kramer et. al [20] developed a new hybrid iterated local search for the PRP addressed in Bektaş and Laporte [1]. Since speed has a major impact on CO_2 emissions, the main objective in the PRP is to optimize vehicle speed for each route. Kramer et. al [20] considered the same speed on each arc and assumed that the departure time is fixed. Kramer et. al [19] extended the previous work by introducing variable departure times. Moreover, speed and departure time are both embedded in the optimization algorithm proposed in Kramer et. al [20]. Table 1 summarizes the main papers on the PRP and its variants.

1.2 Literature review on the G-VRPs with alternative fuel vehicles

Since the transport sector has a heavy environmental impact, and usually companies do not compensate for their emission costs, reducing the CO_2 emissions constitutes a challenge for governments. In recent years several companies have started using alternative fuel vehicles (AFVs), especially electric vehicles (EVs), instead of conventional ones, as a result of governmental incentives (see Pelletier et al. [29]). While EVs do not produce CO_2 emissions and are more silent than conventional vehicles, they are constrained by the low autonomy of their battery, the limited number of public charging stations (CSs) and long charging times.

Gonçalves et al. [13] studied a VRP variant with pickup and delivery, and a mixed fleet composed of EVs and conventional vehicles. Charging can be done at any time during a route and each EV has a fixed autonomy and charging time. They applied their model to a particular case of a Portuguese battery distributor and studied three different scenarios: in the first one they considered only the company's conventional fleet, in the second one the fleet is composed of conventional vehicles and uncapacitated EVs, while in the third one they use only EVs. Conrad and Figliozzi [3] introduced the recharging VRP with time windows, where the vehicles have to be charged at some customer locations in order to continue their route. Energy consumption and travelled distance are is proportional to traveled distance. Recharging is allowed while servicing customers.

Erdoğan and Miller-Hooks [8] defined the Green VRP (GVRP) in which the fleet is composed of alternative fuel vehicles. The vehicle fuel tank can be charged at alternative fuel charging stations, and fuel consumption is proportional to travelled distance. Schneider et al. [33] extended this work by introducing the Electric-VRP (E-VRP) with time windows (E-VRPTW) and recharging stations, in which EVs can be charged at any of the available CSs. Charging time is not fixed, but is related to the battery state of charge when the vehicle arrives at the CS. Felipe et al. [9], extended the model presented in Erdoğan and Miller-Hooks [8] in a different way. They allowed partial recharges at the stations and considered multiple charging technologies.

Sassi et al. [30] formulated the heterogeneous electric vehicle routing problem with time dependent charging costs and a mixed fleet, in which a set of customers have to be served by a mixed fleet of vehicles composed of conventional vehicles and EVs. The EVs have different battery capacities and operating costs. An EV can be charged at the available CSs only if it is compatible with the available technologies. Partial recharges

Table 1: Summary of the literature on the PRP and its variants

Reference	Algorithm	Mathematical model	Time windows	Time dependency	Pickup & delivery	Heterogeneous fleet	Uncertain data
Bektaş and Laporte [1]		•	•				
Figliozzi [10]	Heuristic	•	•	•			
Demir et al. [4]	Heuristic	•	•				
Jabali et al. [15]	Heuristic			•			
Demir et al. [5]	Heuristic	•	•				
Franceschetti et al. [11]			•	•			
Tajik et al. [35]		•	•		•		•
Koç et al. [17]	Heuristic	•	•			•	
Kramer et al. [20]	Heuristic	•	•				
Kramer et al. [19]	Heuristic						

and recharges at the depot are allowed. Charging costs vary according to station and time of day. A mixed fleet of conventional vehicles and EVs are also considered in Goeke and Schneider [12]. The authors formulated the E-VRP with time windows and mixed fleet, in which the EVs can be charged at the available CSs. Charging times vary according to the battery level when the EV arrives at the CS and charging is always done up to maximum battery capacity. The authors proposed a realistic energy consumption model which considers speed, vehicle mass and gradient. They modeled three different objective functions: the first one minimizes the travelled distance, the second one the energy and labor costs, and the third one also includes the cost related to the battery replacement after the depreciation.

Li-ying and Yuan-bin [22] introduced the EV multiple charging station location-routing problem with time windows whose aim is to optimize the EV routing plan and the CSs location strategy. In particular, they also considered the possibility of choosing among the different types of charging infrastructures. Ding et al. [7] extended the E-VRPTW model of Schneider et al. [33] by introducing partial charging and a pickup and delivery policy. Bruglieri et al. [2] presented a variant of E-VRPTW in which the battery charging level is a decision variable. Desaulniers et al. [6] extended the E-VRPTW by considering four charging strategies: a single charge or multiple charges per route and fully recharge only, multiple recharges per route and batteries are fully charged, at most a single recharge per route and partial recharges, and multiple partial recharges. Lin et al. [25] extended the E-VRP by considering a heterogenoeus fleet of EVs and the vehicle load effect on battery consumption as in Goeke and Schneider [12].

Hiermann et al. [14] introduced the electric fleet size and mix vehicle routing problem with time windows and recharging stations. They considered a heterogeneous fleet of EVs in which each vehicle is characterised by its fixed cost, battery and load capacity, energy consumption and charging rate. Each vehicle can be fully charged at a CS. Keskin and Çatay [16] formulated the E-VRPTW with partial recharges and solved it by means of an ALNS metaheuristic. Koç and Karaoglan [18] proposed a new formulation for the G-VRP introduced by Erdoğan and Miller-Hooks [8], with new decision variables in order to allow multiple visits to the CSs without augmenting the networks with dummy nodes. Based on this work, Leggieri and Haouari [21], proposed a new formulation for the E-VRPTW.

Montoya et al. [26] developed a multi-space sampling heuristic for the G-VRP introduced by Erdoğan and Miller-Hooks [8]. They performed several computational tests and compared their approach with those of Erdoğan and Miller-Hooks [8] and Schneider et al. [33] and concluded that their heuristic is not only highly competitive, but also the simplest one for the G-VRP. All early E-VRP models assumed that the battery charge level is a linear function of charging time, while in reality it is non-linear. Montoya et al. [27] extended the classical E-VRP by considering a non-linear charging function and proposed an iterated local search enhanced with a heuristic concentration for the problem. They conducted several computational experiments by comparing their proposed non-linear charging function to those used in previous models. They concluded that a linear charging function may lead to infeasible or expensive solutions.

The decisions about the location and technology of the CSs are directly related to EV routing. The installation and operation costs of the network highly impact on the companies' decisions. Yang and Sun [37] introduced the electric vehicles battery swap stations location routing problem whose aim is to determine the locations of battery swap stations (BSSs), as well as the routing plan of EVs. The CS locations and the selection of charging infrastructure types are two critical factors in the E-VRP. Their joint optimization may have a major impact on logistics costs. Paz et al. [28] introduced the multi-depot electric vehicle location–routing problem with time windows in which a homogeneous fleet of EVs is considered. The goal is to determine the number and location of CSs and depots, as well as the number of EVs and their routes. The authors also considered the possibility of charging the EV at a CS or to swap the battery at a BSS. Hence they proposed and tested three models: in the first one the conventional partial or complete charges can be done at the depots or at the customer locations, in the second one the batteries can be swapped only at the depots, while in the third one if a charging vertex is activated, then it is a BSS and a customer vertex is activated only for the conventional recharging.

Schiffer and Walther [32] introduced the electric location routing problem with time windows and partial recharging in which the the EVs can be charged at any node in the network with only one type of technology. The authors modeled three objective functions: the first one minimizes the total traveled distance, the second one minimizes the number of EVs, and the third one minimizes the number of CSs. Schiffer and Walther [31] defined the location routing problem with intra-route facilities which focuses on determining the location of facilities for intermediate stops. These facilities are not depots and do not necessarily coincide with customers. Intra-route facilities allow for intermediate stops on a route in order to keep the vehicle operational. Table 2 summarizes the main papers on the G-VRP and its variants. For a more complete survey, the reader is referred to Lin et al. [24].

1.3 Scientific contribution and organization of this paper

In this paper, we investigate a GVRP variant in which we consider a mixed vehicle fleet composed of ECVs and conventional internal combustion commercial vehicles (ICCVs). The literature on the VRP with a fleet composed of both ECVs and ICCVs is very limited (see Table 3 for a summary). In the majority of the aforementioned works, the authors suppose that the EVCs battery must be fully recharged. Moreover, while Goeke and

Table 2: Summary of the literature on the G-VRP variants

Reference	Algorithm	Math model	Time windows	Fixed charging	Partial recharge	Location of CSs	Multiple technologies	Battery swap	Linear charging	Non-linear charging	Energy consumption linear to distance	Energy consumption model	Pickup & delivery	Multi-depot	Mixed fleet (EVs and ICCVs)
Gonçalves et al. [13]		•		•							•		•		•
Conrad and Figliozzi [3]	Heuristic	•	•						•		•				
Erdoğan and Miller-Hooks [8]	Heuristic	•		•							•				
Schneider et al. [33]	Heuristic	•	•						•		•				
Felipe et al. [9]	Heuristic	•			•		•		•		•				
Sassi et al. [30]	Heuristic	•	•		•				•		•				•
Goeke and Schneider [12]	Heuristic	•	•						•			•			•
Yang and Sun [37]	Heuristic	•						•			•				
Li-ying and Yuan-bin [22]	Heuristic	•	•			•	•		•		•				
Ding et al. [7]	Heuristic	•	•		•				•		•		•		
Bruglieri et al. [2]	Heuristic	•	•						•		•				
Desaulniers et al. [6]	Exact	•	•		•				•		•				
Lin et al. [25]		•							•			•	•		
Hierman et al. [14]	Heuristic	•	•								•				
Keskin and Çatay [16]	Heuristic	•	•						•		•				
Koç and Karaoglan [18]	Exact			•							•				
Montoya et al. [26]	Heuristic			•							•				
Montoya et al. [27]	Heuristic	•					•			•	•				
Schiffer and Walther [32]	Exact	•			•				•		•				
Schiffer and Walther [31]	Heurisic	•	•		•	•			•		•				
Leggieri and Haouari [21]	Exact	•		•							•				
Paz et al. [28]		•	•		•	•		•	•		•			•	

Schneider [12] modelled a realistic energy consumption for both the ECVs and ICCVs, the other works do not consider the impact of ICCVs polluting emissions. Since the ECVs have a limited autonomy, and a full battery recharge requires a long time, as in Montoya et al. [27] we assume that the ECVs can be partially recharged at any of the available stations. Referring to the ICCVs, we model the polluting emissions through a function of both travelled distance and vehicle load. Furthermore, we consider customer time windows and limited vehicle freight capacities. The objective of the model is the minimization of an objective function that takes into account recharging, routing, and activation of ECVs costs. In addition, the overall pollution emissions are maintained within a given limit. In contrast with previous studies that have focused on routing costs and energy consumption, our work explicitly accounts for polluting emissions through an upper bound constraint that can be parametrized. In order to solve the problem under investigation, we propose an iterative local search metaheuristic.

The remainder of this paper is organized as follows. Section 2 is devoted to the description of a mathematical model for the green mixed fleet vehicle routing problem with partial battery recharging and time windows. Section 3 provides a general description of the iterated local search metaheuristic, whereas the computational experiments are reported in Section 4. Conclusions follow in Section 5.

2 The green mixed fleet vehicle routing problem with partial battery recharging and time windows (GMFVRP-PRTW)

We formulate our problem as follows. Let $\mathcal{N}$ be the set of customers, and $\mathcal{R}$ the set of recharging stations. We will also need σ copies of recharging stations to account for multiple visits at the same station, where σ is an input parameter. Thus, let $\mathcal{R}'$ be the set of all stations and their copies, i.e. $|\mathcal{R}'| = |\mathcal{R}|\ (1+\sigma)$. The value $1+\sigma$ corresponds to the number of times each station can be visited. Let $\mathcal{V} = \mathcal{R} \cup \mathcal{N}$ and $\mathcal{V}' = \mathcal{N} \cup \mathcal{R}'$. The problem is defined on the graph $\mathcal{G}(\mathcal{V}', \mathcal{A})$, where $\mathcal{A} = \{(i,j) : i,j \in \mathcal{V}', i \neq j\}$ is the set of arcs. The depot is a particular element belonging to the set $\mathcal{R}'$, that is the recharging station where vehicle routes start and end. We duplicate the depot and denote by s the starting node and by t the ending node. A heterogeneous fleet of vehicles, composed of n^E ECVs and n^C ICCVs is available. In what follows the superscripts C and E stand for conventional and electric vehicles, respectively. All customers must be visited by a single vehicle. Every customer $i \in N$ has a demand q_i [kg] and a service time s_i [hours].

Each node $i \in \mathcal{V}'$ has a time window $[e_i, l_i]$. For each $(i,j) \in \mathcal{A}$, d_{ij} denotes the distance from i to j [km], while t_{ij} is the travel time from i to j [hours], c_{ij}^E and c_{ij}^C denote the

Table 3: Summary of the literature on the Mixed Fleet G-VRP and its variants

Reference	Algorithm	Math model	Time windows	Fixed charging	Partial recharge	Multiple technologies	Linear charging	Energy consumption proportioned to distance	Energy consumption model	Pickup & delivery	Polluting emissions
Gonçalves et al. [13]		•		•				•		•	
Sassi et al. [30]	Heuristic	•	•		•		•	•			
Goeke and Schneider [12]	Heuristic	•	•				•		•		
This paper	Heuristic	•	•		•	•	•	•			•

travel cost [€/km] for the electrical and conventional vehicles respectively. We impose a limit T on the duration of a route [hours], that is, the end of the time window associated with the depot node is set equal to T.

The vehicles (electrical and conventional) are characterized by different loading capacities, denoted as Q^E and Q^C [kg] for the ECVs and ICCVs, respectively. Furthermore, for each ECV let B^E denote the maximum battery capacity [kWh]. The recharging cost w^r is assumed to be constant and the same for all stations. All recharging stations $i \in \mathcal{R}'$ are characterized by a recharging speed ρ_i [kWh per hour]. We denote by π the coefficient of energy consumption, assumed to be proportional to the distance traveled [€/km]. Partial battery recharging is allowed at any recharging station. Referring to the ICCV, we consider a limit on the overall CO_2 emissions [kg].

2.1 The emission factor for the conventional vehicles

In order to define a fuel consumption model for the ICCVs, we have to introduce the emission factor. As in Ubeda et al. [36], we assume that the calculation of CO_2 emissions depends on two factors: the type of vehicle and the type and quantity of fuel consumed. In fact, the CO_2 emissions vary according to the type of transport, in particular the mass of the vehicle, the distance traveled and the load carried.

In order to estimate the emission factor, it is important to calculate the fuel conversion factor. For this purpose we use the chemical reaction proposed by Lichty [23]. Once we have calculated the fuel conversion factor, that is 2.61 CO_2/ litre of diesel, it is possible to estimate the emission factor ε. Thus we define a function, taking into account data related to the average fuel consumption, which depends on the load. The emission factor ε is equal to the emission factor multiplied by the consumption of diesel fuel. Table 4 shows the estimation of emission factors for several capacity scenarios for a 10 tonne capacity vehicle (see Ubeda et al. [36]).

Load of the vehicle	Weight laden (%)	Consumption (litre/100km)	Emission factor (kg CO_2/km)
Empty	0	29.6	0.77
Low loaded	25	34.0	0.83
Half loaded	50	34.4	0.90
High loaded	75	36.7	0.95
Full load	100	39.0	1.01

Table 4: Estimation of emission factors for a truck with 10-tonne capacity

2.2 The GMFVRP-PRTW model

In order to model the GMFVRP-PRTW we define decision variables as follows:

$$x^E_{ij} = \begin{cases} 1, & \text{the ECV travels from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases} \quad (i,j) \in \mathcal{A}$$

$$x^C_{ij} = \begin{cases} 1, & \text{the ICCV travels from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases} \quad (i,j) \in \mathcal{A}$$

z_{ij} amount of energy available when arriving at node j from the node i [kWh], $(i,j) \in \mathcal{A}$
g_{ij} amount of energy recharged by the ECV at the node i for travelling to j [kWh], $i \in \mathcal{R}, j \in \mathcal{V}'$
τ_j arrival time of the vehicle to the node j [hours], $j \in \mathcal{V}'$
u^C_i amount of load left in the vehicle after visiting node i [kg], $i \in \mathcal{V}'$
u^E_i amount of load left in the vehicle after visiting node i [kg], $i \in \mathcal{V}'$.

Starting from the consideration introduced in Section 2.1, we define emission functions $\varepsilon(u^C_i)$ that depends on the load on the vehicle at node i. For instance, if variable u^C_i assumes a value in the range $[0, 0.25Q^C]$, then $\varepsilon(u^C_i) = 0.77$ (see Table 4). The value $\sum_{(i,j)\in\mathcal{A}} \varepsilon(u^C_i) d_{ij} x^C_{ij}$ represents the total pollution emissions.

The mixed integer program that models our problem is as follows:

$$\text{Minimize} \quad w^r \sum_{i\in\mathcal{R}'} \sum_{j\in\mathcal{V}'} g_{ij} + w^a \sum_{j\in\mathcal{V}'} x^E_{sj} + \sum_{(i,j)\in\mathcal{A}} c^E_{ij} d_{ij} x^E_{ij} + \sum_{(i,j)\in\mathcal{A}} c^C_{ij} d_{ij} x^C_{ij} \tag{1}$$

$$\text{subject to} \quad \sum_{j\in\mathcal{V}'} (x^E_{ij} + x^C_{ij}) = 1 \qquad i \in \mathcal{N} \tag{2}$$

$$\sum_{j\in\mathcal{V}'} x^E_{ij} \leq 1 \qquad i \in \mathcal{R}' \tag{3}$$

$$\sum_{j\in\mathcal{V}'\setminus\{s\}} x^E_{ij} - \sum_{j\in\mathcal{V}'\setminus\{t\}} x^E_{ji} = 0 \qquad i \in \mathcal{V}' \tag{4}$$

$$\sum_{j\in\mathcal{V}\setminus\{s\}} x^C_{ij} - \sum_{j\in\mathcal{V}\setminus\{t\}} x^C_{ji} = 0 \qquad i \in \mathcal{V} \tag{5}$$

$$\sum_{j\in\mathcal{V}'} x^E_{sj} \leq n^E \tag{6}$$

$$\sum_{j\in\mathcal{V}} x^C_{sj} \leq n^C \tag{7}$$

$$\sum_{i\in\mathcal{V}' i\neq s} x^E_{si} - \sum_{j\in\mathcal{V}' j\neq t} x^E_{jt} = 0 \tag{8}$$

$$\sum_{i\in\mathcal{V} i\neq s} x^C_{si} - \sum_{j\in\mathcal{V} j\neq t} x^C_{jt} = 0 \tag{9}$$

$$u^E_j \geq u^E_i + q_j x^E_{ij} - Q^E(1 - x^E_{ij}) \qquad i \in \mathcal{V}' \setminus \{s,t\}, j \in \mathcal{V}' \setminus \{s\} \tag{10}$$

$$u^C_j \geq u^C_i + q_j x^C_{ij} - Q^C(1 - x^C_{ij}) \qquad i \in \mathcal{V} \setminus \{s,t\}, j \in \mathcal{V} \setminus \{s\} \tag{11}$$

$$u^E_j \leq Q^E \qquad j \in \mathcal{V}' \tag{12}$$

$$u^C_j \leq Q^C \qquad j \in \mathcal{V} \tag{13}$$

$$u^E_s = 0 \tag{14}$$

$$u^C_s = 0 \tag{15}$$

$$\tau_j \geq \tau_i + (t_{ij} + s_i) x^E_{ij} - M(1 - x^E_{ij}) \qquad i \in \mathcal{N}, j \in \mathcal{V}' \tag{16}$$

$$\tau_j \geq \tau_i + (t_{ij} + s_i) x^C_{ij} - M(1 - x^C_{ij}) \qquad i \in \mathcal{V}, j \in \mathcal{V} \tag{17}$$

$$\tau_j \geq \tau_i + t_{ij} x^E_{ij} + \frac{1}{\rho_i} g_{ij} - M(1 - x^E_{ij}) \qquad i \in \mathcal{R}', j \in \mathcal{V}' \tag{18}$$

$$e_j \leq \tau_j \leq l_j \qquad j \in \mathcal{V}' \tag{19}$$

$$z_{ij} \leq (z_{hi} + g_{ij}) - \pi d_{ij} x^E_{ij} + M(1 - x^E_{ij}) + M(1 - x^E_{hi}) \qquad h \in \mathcal{V}', \; i \in \mathcal{V}' \setminus \{s\}, \; j \in \mathcal{V}', i \neq j, i \neq h, j \neq h \tag{20}$$

$$z_{sj} \leq B^E - \pi d_{sj} x^E_{sj} + M(1 - x^E_{sj}) \qquad j \in \mathcal{V}' \tag{21}$$

$$g_{ij} \leq B^E - z_{hi} + M(1 - x^E_{ij}) + M(1 - x^E_{hi}) \qquad i \in \mathcal{R}' \setminus \{s\}, h \in \mathcal{V}', j \in \mathcal{V}' \tag{22}$$

$$z_{ij} \geq 0.1 B^E \qquad i \in \mathcal{R}', j \in \mathcal{V}' \tag{23}$$

$$g_{ij} \leq 0.9 B^E \qquad i \in \mathcal{R}', j \in \mathcal{V}' \tag{24}$$

$$\sum_{(i,j)\in\mathcal{A}} \varepsilon(u^C_i) d_{ij} x^C_{ij} \leq UB \tag{25}$$

$$x^E_{ij}, x^C_{ij} \in \{0,1\}, i \in \mathcal{V}', j \in \mathcal{V}'; u^E_i, u^C_i, \tau_i \geq 0, i \in \mathcal{V}' \tag{26}$$

$$g_{ij} \geq 0, i \in \mathcal{R}', j \in \mathcal{V}'.$$

The objective function is the sum of four terms. The first one is the cost [€] of energy recharged at all the recharging stations. The second term takes into account the activation of ECVs. The cost w^a is the vehicle activation cost, which depends on the battery capacity of the vehicle. In particular we assume that $w^a = B^E w^r$, that is the cost of one complete recharge of the vehicle. The third and fourth terms represent the cost of the routes traveled by the ECVs and the ICCVs, respectively.

Constraints (2) ensure that each customer is visited exactly once, whereas conditions (3) mean that each copy of a recharging station can be visited at most once. Constraints (4) and (5) are the flow conservations constraints, whereas (6) and (7) ensure that the total number of vehicles used in the solution (electrical and conventional, respectively) does not exceed the fleet size. Constraints (8)–(9) ensure that the route of each vehicle starts and ends at the depot. Conditions (10)–(15) represent the capacity constraints, for the ECVs and ICCVs, respectively. Constraints (16)–(18) define the variables τ, whereas the time windows constraints are specified by (19). Constraints (20) and (21) define the variables z ensuring that the capacity of the battery is not exceeded, and conditions (22) are used to represent the partial battery recharging. Constraints (23) and (24) define the state of charge of the battery. Finally, constraints (25) impose a limit on the pollution emissions. In particular, $\varepsilon(u_i^C)$ is the emission function previously introduced. Constraints (27) define the domains of variables.

3 The Iterated Local Search Metaheuristic

The proposed metaheuristic is based on iterated local search (ILS). The general structure of the ILS is detailed in Algorithm 1. We are given a set $\mathcal{N}$ of customers to be served. These are partitioned into two clusters, one served by the ICCVs ($C^{'}$), the other by the ECVs ($E^{'}$). Here a route is defined as an ordered set of nodes so that union operators can be applied to routes. The ILS generates an initial solution η_0, as a set of routes, and while the stopping criterion is not satisfied, a perturbation and the local search procedures are applied. Finally, the best solution η^* is returned, that is, a set of routes with the best total cost.

Algorithm 1 . Iterated local search (ILS)

```
Generate the initial solution η_0
Apply the local search procedure
while Stop criterion is not verified do
  Perturbation
  Local search
end while
return best solution η*
```

Initialization Phase In order to generate an initial solution, we propose a constructive heuristic based on Solomon's sequential insertion heuristic SIH [34]. Algorithm 2 presents the general structure of the SIH. This heuristic identifies both the node u^* to be added to the initialized route and the position of the insertion. In order to choose u^*, SIH considers the insertion position for all the unrouted nodes $\mathcal{N}^-$ by evaluating both the insertion cost and the associated time delay to serve the subsequent customers.

Given the use of a heterogeneous fleet in our problem, after the definition of two clusters of customers which will be served by the electric vehicles and the conventional vehicles respectively, the constructive heuristic is divided into two different phases. The former is aimed at defining the routes used to serve the customers with the ICCVs (i.e., conventional routes η_c) while in the latter, the routes for the customers served by the ECVs (i.e. electrical routes η_e) are built. Finally, the solution $\eta^{'} = \eta_c \cup \eta_e$ is returned.

Algorithm 2 . Sequential insertion heuristic (SIH)

1. Clustering $(\mathcal{N}) \rightarrow C^{'}, E^{'}$
2. Insertion heuristic $(C^{'}) \rightarrow \eta_c$
if some customers are not served **then**
  update $E^{'} : E^{'} \cup \{\mathcal{N}^-\}$
end if
3. Insertion heuristic $(E^{'}) \rightarrow \eta_e$
return solution $\eta^{'} = \eta_c \cup \eta_e$

Clustering Algorithm The main aim of this algorithm is to build two clusters of customers $C^{'}$ and $E^{'}$, which will be served by the electrical and conventional vehicles, respectively. Given the set of customers $\mathcal{N}$ to be served, the procedure determines two subsets $E^{'} \subseteq \mathcal{N}$ and $C^{'} \subseteq \mathcal{N}$, such that $E^{'} \cap C^{'} = \emptyset$ and $E^{'} \cup C^{'} = \mathcal{N}$. In order to define $E^{'}$ and $C^{'}$, let we use of two sets E and C, defined by the start node s. Two scores, called p_i^E $(1 \leq p_i^E \leq 10)$ and p_i^C $(1 \leq p_i^C \leq 10)$, are used in the clustering algorithm. The first score is calculated as

$$p_i^E = 11 - \left(1 + \frac{d_i^E - d_{\text{min}}^E}{d_{\text{max}}^E - d_{\text{min}}^E} \times 9\right), \tag{27}$$

where d_i^E is the distance between the customer i and the barycentre b_e of the set E, d_{min}^E is the distance between b_e and the nearest customer $j \in N$, while d_{max}^E is the distance between b_e and the farthest customer $j \in N$. The second score is calculated as

$$p_i^C = \lambda(pDist_i^C) + (1 - \lambda)(pQ_i), \tag{28}$$

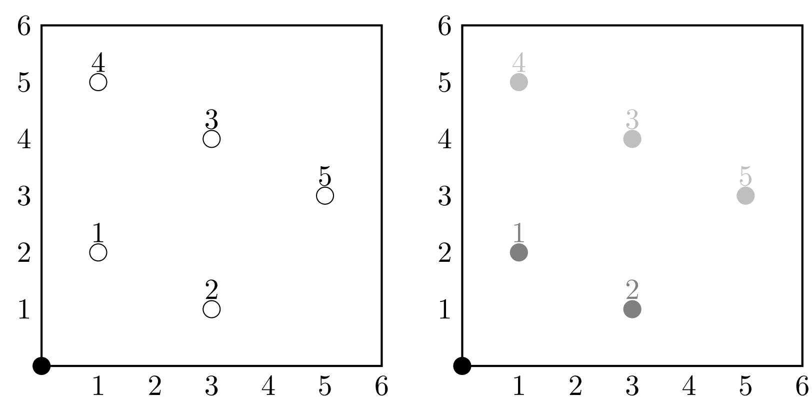
where $0 \leq \lambda \leq 1$, $pDist_i^C = 11 - \left(1 + \frac{d_i^C - d_{\text{min}}^C}{d_{\text{max}}^C - d_{\text{min}}^C} \times 9\right)$, $pQ_i = 11 - \left(1 + \frac{q_i - q_{min}}{q_{\text{max}} - q_{\text{min}}} \times 9\right)$, d_i^C is the distance between the customer i and the barycentre b_c of the set C, d_{min}^C is the distance between b_c and the nearest customer $j \in N$, d_{max}^C is the distance between b_c and the farther customer $j \in N$, q_i is the demand of customer i, $q_{\min}$ is the smallest customer demand, and $q_{\max}$ is the largest customer demand.

After the evaluation of the score of each customer, it is possible to define the two clusters. For each cluster, select at each iteration the customers with the maximum score: $i^*_E = \text{argmax}_{i \in N \setminus C' \cup E'}\{p^E_i\}$, then $i^*_C = \text{argmax}_{i \in N \setminus C' \cup E'}\{p^C_i\}$. If $i^*_E \neq i^*_C$, i^*_E is assigned to E, and i^*_C to C. Otherwise, if $p^E_{i^*_E} > p^C_{i^*_C}$ i^* is assigned to E, else if $p^E_{i^*_E} \leq p^C_{i^*_C}$ i^*, the node is assigned to C. The barycentre for each cluster is recalculated and the scores for the unassigned nodes are recomputed at the end of each iteration. The two final clusters $E^{'}$ and $C^{'}$ are obtained by removing node s from cluster E and C, respectively.

Example 3.1 shows the steps of the proposed clustering procedure on a toy instance.

Example 3.1 *Let us consider the instance depicted in Figure 1(a) where five customers have to be served starting from the depot s. The number over each circle represents the id of the associated customer. Since the score p^E_i and the parameter $pDist^C_i$, used to calculate the score p^C_i, are computed by considering the distances among the nodes, we report in Figure 1 the spatial deployment of the customers in the considered square field. The demand, used to calculate pQ^C_i, and the coordinate (x, y) associated with each customer are reported in Table 1.*

Figure 1: Toy instance. The black circle represents the depot.



(a) Spatial representation of the toy instance.

(b) Clustering solution. The nodes in light gray represent customers belonging the set $C^{'}$, the gray ones represent customers belonging the set $E^{'}$.

Table 6 reports the sets C and E at the beginning of each iteration under the column "Initial set", the barycentres b_e and b_c under column b, the values of d_{max} and d_{min}, the scores under the column p_1 to p_5, the set C and E at the end of each iteration under the *column "Final set".*

Table 5: Characteristics of the customers for the toy instance depicted in Figure 1

Depot/customers	s	1	2	3	4	5
x	0	1	3	3	1	5
y	0	2	1	4	5	3
Demand	0	30	20	10	5	10

Table 6: Information used in the clustering procedure for solving the toy instance depicted in Figure 1.

Iter	Vehicle typology	Initial set	b	d_{max} d_{min}	p_1	p_2	p_3	p_4	p_5	Final set
1	Conventional	$C = \{s\}$	$(0, 0)$	5.83 2.24	5.50	6.14	5.64	**6.42**	4.60	$C = \{s, 4\}$
	Electrical	$E = \{s\}$	$(0, 0)$	5.83 2.24	**10.00**	7.68	3.08	2.83	1.00	$E = \{s, 1\}$
2	Conventional	$C = \{s, 4\}$	$(0.5, 1)$	4.53 0.71		4.70	**6.50**		4.60	$C = \{s, 4, 3\}$
	Electrical	$E = \{s, 1\}$	$(0.5, 2.5)$	4.92 1.12		**6.73**	3.41		1.00	$E = \{s, 1, 2\}$
3	Conventional	$C = \{s, 4, 3\}$	$(1.\bar{3}, 3)$	3.67 1.05					**4.60**	$C' = \{4, 3, 5\}$
	Electrical	$E = \{s, 1, 2\}$	$(1.\bar{3}, 1)$	4.18 1.05					1.00	$E' = \{1, 2\}$

The highest score for clusters C and E is obtained for customers 4 and 1, respectively which are added to the corresponding set at the first iteration. The barycentres are computed for both clusters C and E at the second iteration. Customers 3 and 2 are added to clusters C and E, respectively. Customer 5 has scores $p_5^C = 4.60$ and $p_5^E = 1.00$, and is therefore added to cluster E. All customers have been assigned to some cluster at the end of the third iteration, and the procedure returns the clusters $C^{'} = \{4, 3, 5\}$ and $E^{'} = \{1, 2\}$. A spatial representation of the clustering solution is reported in Figure 1(b).

Insertion strategy for conventional routes This heuristic chooses the best customer u^* to be added into the route, by taking into account the increase in the traveled distance and traveled time. The heuristic initializes the route as follows: $Z_k = \{s, i^{'}, t\}$, where $i^{'} \in C^{'}$ is the unserved node with the smallest $l_{i^{'}}$. Let $Z_k = \{s, i_1, i_2, \ldots, i_m\}$ be the current route. For each unserved customer $u \in C^{'}$, calculate the best position $f_1(i(u), u, j(u))$ inside the current route Z_k as

$$f_1(i(u), u, j(u)) = \min_{p=1,\ldots,m}\{f_1(i_{p-1}, u, i_p)\}, \qquad (29)$$

where $i(u)$ and $j(u)$ are two adjacent customers into the current route. The customer u^* that will be inserted into the route is the one with the best score:

$$f_2(i(u^*), u^*, j(u^*)) = \max_u\{f_2(i(u), u, j(u))\}, \tag{30}$$

where

$$f_2(i(u), u, j(u)) = c_{s,u} - f_1(i(u), u, j(u)). \tag{31}$$

Before inserting u^* in the route, it is necessary to verify the feasibility of the new solution. If the insertion is infeasible, the algorithm evaluates the possibility of initializing a new route. Otherwise, the customer will be served by the ECVs.

Insertion strategy for electrical routes If some customers belonging to cluster $C^{'}$ are not served by conventional vehicles, they are inserted in cluster $E^{'}$. For each unserved customer $u \in C^{'}$, the best position in the current route is calculated.

The heuristic initializes the route as follow: $Z_w^E = \{s, i^{'}, t\}$, where$i^{'} \in E^{'}$ is the unserved customers with the smallest $l_{i^{'}}$. Let $Z_w^E = (s, i_1, i_2, \ldots, i_m)$ be the current route. For each unserved customer $u \in C^{'}$ we calculate the best position inside the current route Z_k by using [30] and the best node u^* by using [31]. If the insertion of u^* satisfies the capacity and time windows constraints, it can be added to the route.

After this step, it is necessary to check the satisfaction of the energy capacity constraints. If necessary, recharge stations may be added to the route. In particular, if it is not possible to reach the next node, because of the low battery charge, the nearest recharge station is added to the route and the vehicle is recharged as much as necessary to reach the next node.

After the insertion of the recharge stations, it is necessary to verify the time windows constraints. If the constraints are respected but some customers are unserved, a new route is initialized. Otherwise, if some constraints are violated, the solution is repaired by removing customers and recharge stations until it becomes feasible. If the heuristic is unable to find a feasible solution, the unserved customers are added to the conventional routes by violating the emission constraints.

Local Search and Perturbation In order to explore the neighborhood, we introduce an improvement heuristic based on local search procedures. The steps are detailed in Algorithm 3. We start from the solution $\eta^{'}$ created by SIH. If $\eta^{'}$ is feasible, we apply the improvement heuristic and we return it as the best final solution η^*. Otherwise, we apply the improvement heuristic with penalty function and we return the best generated feasible solution η^*.

Algorithm 3 . Local search (LS)

$\eta^{'}$ initial solution generated by SIH
if $(\eta^{'})$ feasible **then**
  Improvement heuristic $(\eta^{'}) \rightarrow \eta^{*}$
else
  Improvement heuristic with penalty function $(\eta^{'}) \rightarrow \eta^{*}$
end if
return best solution η^{*}

Improvement Heuristic A local search method is applied to the initial solution, built by using the constructive heuristic, described in the previous section. It uses the following strategies:

1. **Change of nodes belonging to the conventional routes**: iteratively, for each conventional route, evaluate the best possible insertion of one of its nodes into the other conventional routes. Thus a node is relocated from a conventional route to another conventional route in the best possible position.

2. **Change of nodes belonging to the electrical routes**: for each electrical route, evaluate the best possible insertion of its nodes into the other electrical routes. Thus a node of an electrical route is relocated in another electrical route in the best possible position. It is worth observing that the insertion/removal of a node into/from an electrical route can imply also the insertion/removal of new recharge stations into/from the solution.

3. **Change of nodes belonging to the conventional and electrical routes**: for each route, iteratively evaluate the best possible insertion of one of its nodes into the other conventional or electrical routes. Thus a node is relocated in another conventional or electrical route in the best possible position.

The perturbation is performed by using the same strategies as those implemented in the local search phase. However, during the perturbation, worsenings of the solutions are accepted in order to better explore the neighborhood. The stopping criterion is satisfied when a fixed maximum number of iterations has been reached.

Improvement heuristic with penalty function This alternative approach allows the generation of infeasible solutions in the initialization phase. In particular, the pollution emission constraints are relaxed and the objective function is modified in order to take the penalty cost into account as

$$z^{'}(\eta) = z(\eta) + \theta e(\eta), \tag{32}$$

where $z(\eta)$ is the cost function, θ is the penalty factor, and $e(\eta)$ is the violation of emissions, calculated as

$$e(\eta) = \max\{0, \sum_{(i,j)\in A} \epsilon(u_i^c) d_{ij} x_{ij}^c - UB\}. \tag{33}$$

The penalty factor is set equal to 1 and is adjusted at each iteration of the local search as follows: if after one iteration a constraint violation is still verified, the factor is increased by 10%.

Starting from an infeasible solution generated by the constructive heuristic, the ILS efficiently explores the solutions space until a good quality feasible solution has been identified. For both the local search procedure and the perturbation, the improvement strategies previously described is used. At each iteration, the strategy to be applied is randomly chosen. The algorithm terminates after a fixed number of iterations. Among all feasible solutions, the best one η^* is that with the minimum cost.

4 Computational study

We now analyse the influence of the main features of the problem (i.e. time windows, pollution emissions and partial recharging) on solution configuration and costs, and on the behaviour of the proposed heuristic. We tested our algorithm on instances inspired from those described in the scientific literature. In Section 4.1 we provide a detailed description of these instances. We solved the model with CPLEX 12.5, and implemented the algorithm in Java. We carried out our tests on a PC Intel CoreTM I7-4710 CPU at 2.5 GHz having 16 GB of RAM under Windows 8.1 operating system. Section 4.2 investigates the effects of some parameters of the model on the solution. Section 4.3 describes the computational tests carried out to tune the ILS parameters, whereas a detailed account of the collected computational results is provided in Section 4.4.

4.1 Test instances

The instances used in the computational experiments are the E-VRPTW benchmark instances introduced in [33], based on the well-known VRPTW instances of Solomon [34]. These instances are divided into three classes C, R and RC which differ from one another according to the geographical distribution of the customer locations: a clustered distribution (C), random distribution (R) and a mix of random and clustered structures (RC).

Moreover, C1, R1 and RC1 have a short scheduling horizon, while C2, R2 and RC2 have a long scheduling horizon. Schneider et al. [33] applied some modifications to these instance sets in order to yield the E-VRPTW instances: they first determined in a random manner 21 recharging stations and added them to the test instances, second the battery capacity is suitably set, and third the time windows of some customers are recalculated to ensure feasibility. We carried out our tests by considering two sets of instances. The first one contains the small-size instances considered in [33], with five, 10 and 15 customers. The second set is composed of medium-size instances that have been built starting from five of the 100-customer E-VRPTW instances presented in [33], belonging to the classes C1, R1, RC1. In particular, we kept the 21 recharging stations unchanged and we extracted the first 25 and 30 customers, respectively. As mentioned in Section 1.3, our model enables us to perform a parametric study of the trade-off between operating costs and polluting emissions. This is achieved by multiplying the right-hand side of constraint [25] by a scaling parameter α. For each test instance, we generated three different instances by varying the value of the upper bound on the pollution emissions. In particular, we first calculated an estimate $UB_{\max}$ of the emissions in the worst case; the parameter UB was then set equal to $\alpha \cdot UB_{\max}$, where $\alpha = 0.75, 0.50, 0.25$. Thus, we generated three scenarios: hard, medium and soft constrained, based on the allowed emissions.

In what follows, we refer to *test*"C"nn_α to indicate the network *test* (original name) for which nn customers have been considered and an upper bound on the pollution emissions equal to $\alpha \cdot UB_{\max}$ was imposed. Thus, test instance C101C25_75 is the network C101 for which the first 25 customers were chosen and the limit on the pollution emission is set equal to $0.75 \cdot UB_{\max}$.

We fixed the battery capacity equal to 10 KWh for small-size instances and to 20 KWh for medium- and large-size instances, while the vehicle capacity was fixed at 500 Kg. Whereas a battery recharging operation can be achieved in several ways, with different technologies that imply different times and costs, for our computational tests we assumed that all charging stations have the same characteristics and only one technology is available. This means that the vehicles can be charged in any recharging station by spending the same time, at the same cost. In particular, following Felipe et al. [9] in which different technologies are introduced (slow, medium and fast), we chose the medium technology, hence the recharging speed is fixed at 20,000 KWh/h and the cost is unitary. We also defined a number of σ copies of CSs to allow multiple visits to the same CS. In particular, we iteratively solved our model with CPLEX with increasing values of σ. The procedure stops when no improvement on the solution cost is found. We have conducted several tests on small-size instances and we set the value of σ equal to 1.

4.2 An analysis of model parameters

In this section, we investigate the impact of some model parameters on the optimal solutions. In particular, we have focused on assessing the effect of varying upper bounds on pollution emission on solution cost and configuration, ~~and~~ of evaluating the influence of time windows constraints on the objective function values and computational times, and on evaluating the impact of using partial recharging instead of total recharging on costs and configuration of the solutions.

In Table 7, we report the computational results obtained by solving our model with CPLEX, by varying the value of α. We have set $\alpha = 0.25, 0.50$, and 0.75 and we have calculated the percentage cost variation as $100 \times (c_{\alpha_e} - c_{\alpha_c})/c_{\alpha_c}$, where c_{α_c} and c_{α_e} are the objective function values obtained when α is set equal to α_s and α_e, respectively (see Table 7). The results of Table 7 clearly show that the higher the value of the allowed pollution emissions, the lower is the objective value. In particular, if we consider $\alpha_s = 0.25$ and $\alpha_e = 0.50$, we observe an average cost reduction of about 4.1% on the instances with five customers, and of 3.5% and 2.7% on the instances with 10 and 15 customers, respectively. This reduction is less evident when $\alpha_s = 0.50$ and $\alpha_e = 0.75$. On average, it is about 0.7% for the three classes of test problems.

This trend is strictly related to the number of conventional and electrical vehicles employed, as shown in Table 8, which gives the average number of conventional (#CVs) and electrical (#EVs) used by varying the value of α. The results of Table 8 clearly show that the lower the value of allowed emissions, the higher #EVs and the lower #CVs. On average, when $\alpha = 0.75$ the number of EVs is less than one, while it increases to about two when $\alpha = 0.25$. In contrast, the number of conventional vehicles is about two when $\alpha = 0.75$ and $\alpha = 0.50$, it decreases to about one when $\alpha = 0.25$. It is clear that the routing of EVs is more expensive than the routing of conventional vehicles. However, the cost reduction becomes less significant when $\alpha_s = 0.50$ and $\alpha_e = 0.75$. The results show that in order to find a good trade-off between cost and environmental sustainability, values of α between 0.25 and 0.50 represent the most adequate choice.

Since we carried out the computational experiments on two types of test problems, short scheduling horizon and long scheduling horizon instances, we have also analyzed how the planning horizon length may influence the solution cost, considering different values of α. Table 9 shows the average percentage reduction of the total cost obtained by varying the values of α and the planning horizon length. The table is divided into two parts: short scheduling horizon and long scheduling horizon. In the second column we report the class of tests (five, 10 and 15 customers), in the third and fourth columns the percentage reduction of total cost varying the values of α. Looking at Table 9 it is clear that when we consider instances with a long scheduling horizon, the percentage reduction

Table 7: Percentage reduction of total cost varying the values of α

Test	$\alpha_s = 0.25$ $\alpha_e = 0.50$ Cost variation (percent)	$\alpha_s = 0.50$ $\alpha_e = 0.75$ Cost variation (percent)	Test	$\alpha_s = 0.25$ $\alpha_e = 0.50$ Cost variation (percent)	$\alpha_s = 0.50$ $\alpha_e = 0.75$ Cost variation (percent)	Test	$\alpha_s = 0.25$ $\alpha_e = 0.50$ Cost variation (percent)	$\alpha_s = 0.50$ $\alpha_e = 0.75$ Cost variation (percent)
$C101C5$	-2.2%	0.0%	$C101C10$	-0.7%	-3.5%	$C103C15$	-2.8%	-2.4%
$C103C5$	-3.6%	0.0%	$C104C10$	-8.7%	0.0%	$C106C15$	-2.8%	0.0%
$C206C5$	-0.5%	0.0%	$C202C10$	-4.8%	-1.0%	$C202C15$	-2.0%	-2.6%
$C208C5$	-5.7%	0.0%	$C205C10$	-2.8%	0.0%	$C208C15$	-3.2%	-1.4%
$R104C5$	-3.0%	0.0%	$R102C10$	-0.8%	0.0%	$R202C15$	-0.5%	0.0%
$R105C5$	-0.4%	0.0%	$R103C10$	-1.6%	0.0%	$R209C15$	-1.0%	-0.3%
$R202C5$	-5.0%	0.0%	$R201C10$	-0.5%	-1.9%	$R102C15$	-1.7%	-1.4%
$R203C5$	-6.3%	0.0%	$R203C10$	-8.8%	0.0%	$R105C15$	-3.5%	-1.2%
$RC105C5$	-3.1%	-0.2%	$RC102C10$	-6.3%	-1.3%	$RC103C15$	-1.9%	0.0%
$RC108C5$	-4.4%	0.0%	$RC108C10$	-5.7%	0.0%	$RC108C15$	-5.1%	-1.8%
$RC204C5$	-5.0%	-3.6%	$RC201C10$	-1.1%	-1.0%	$RC202C15$	-4.2%	-2.1%
$RC208C5$	-10.0%	0.0%	$RC205C10$	0.0%	0.0%	$RC204C15$	-3.5%	-2.2%
Average	-4.1%	-0.3%	Average	-3.5%	-0.7%	Average	-2.7%	-1.3%

Table 8: Number of vehicles employed for each value of α

	$\alpha = 0.25$		$\alpha = 0.50$		$\alpha = 0.75$	
Class	#CVs	#EVs	#CVs	#EVs	#CVs	#EVs
$\mid \mathcal{N} \mid=5$	0.50	1.30	1.50	0.60	1.50	0.08
$\mid \mathcal{N} \mid=10$	1.00	1.60	1.80	0.60	2.20	0.00
$\mid \mathcal{N} \mid=15$	1.25	1.75	2.16	0.81	2.75	0.08
Average	0.92	1.55	1.82	0.67	2.15	0.05

obtained by varying α is higher than on the instances with a short scheduling horizon.

In order to analyze how the time windows constraints influences the solutions for our problem, we have performed a computational study by removing the time windows. Since CPLEX was able to solve only instances with at most 10 customers, the computational experiments were carried out on instances with five and 10 customers. The related results are summarized in Table 10, which gives, for each value of α, the average percentage cost variation, defined as $100 \times (c^M - c^{M_R})/c^{M_R}$, where c^M is the cost obtained by solving our model, and c^{M_R} is the cost obtained by solving the relaxed model without time windows constraints. Table 10 also reports the speed-up values, i.e. the ratio between the computational time required by CPLEX to solve the relaxed and the original models. As expected, the solution costs obtained by removing the time windows are lower than those obtained with the original model.

On average, the percentage variation is about 9.5% when $\alpha = 0.25$, 11.13% when $\alpha = 0.50$, and 12.48% when $\alpha = 0.75$. However, the time required by CPLEX to solve the model without time windows is on average 7.13, 5.01 and 2.59 times higher than the time required to solve our model, when $\alpha = 0.25$, $\alpha = 0.50$ and $\alpha = 0.75$, respectively. In conclusion, it is clear that the length of the planning horizon and the time windows both influence the configuration and cost of the solutions. Indeed, when a long time horizon is considered, the values of pollution emissions highly influence the solution costs. One observes the same trend when time windows constraints are not taken into account. In this case the costs are significantly reduced when higher values of polluting emissions are allowed.

Table 9: Average percentage reduction of total cost varying the values of α and the planning horizon length

		$\alpha_s = 0.25$ $\alpha_e = 0.50$	$\alpha_s = 0.50$ $\alpha_e = 0.75$
	Class	Cost variation (percent)	Cost variation (percent)
Short	$\mid \mathcal{N} \mid$=5	-2.8%	0.0%
scheduling	$\mid \mathcal{N} \mid$=10	-4.0%	-0.8%
horizon	$\mid \mathcal{N} \mid$=15	-2.4%	-0.8%
	Average	-3.0%	-0.5%
Long	$\mid \mathcal{N} \mid$=5	-5.4%	-0.6%
scheduling	$\mid \mathcal{N} \mid$=10	-3.0%	-0.6%
horizon	$\mid \mathcal{N} \mid$=15	-3.0%	-1.8%
	Average	-3.8%	-1.0%

Table 10: Average percentage cost variation and speedup on five and 10 customers instances when time windows constrains are not considered

	$\alpha = 0.25$		$\alpha = 0.50$		$\alpha = 0.75$	
Class	Cost variation (percent)	Speed up	Cost variation (percent)	Speed up	Cost variation (percent)	Speed up
$\mid \mathcal{N} \mid$=5	5.25%	1.46	9.32%	1.05	9.30%	1.11
$\mid \mathcal{N} \mid$=10	13.67%	12.81	12.93%	8.96	15.67%	4.07
Average	9.46%	7.13	11.13%	5.01	12.48%	2.59

We finally evaluate the effect of using partial recharging. We have solved the model of Section 2.2 on small-size instances, by imposing the condition that after visiting a recharging station, the battery should be fully recharged. Because when $\alpha = 75\%$ we do not have any visit to the recharge stations for almost all the instances, we have considered two values of α, that is 25% and 50%. In Tables 11 – 13 we compare the results obtained by solving the model with partial recharges with those obtained by solving the model with full recharge. In each table, we report the name of the problem test, the total cost variation calculated as $(c^M_{tot} - c^M)/c^M$, where c^M_{tot} is the value of the objective function obtained by solving the model with full recharging. We also report the cost variation of conventional vehicles and EVs, and in the last column the recharging cost variation. The symbol "–" in Tables 11 – 13 means that the cost related to that parameter is zero. Looking at Tables 11 – 13 it is clear that when α is set to 75% the solutions of the models are the same, indeed in the majority of the instances the EVs are not recharged and the solutions present the same configuration. However, the comparison is highly interesting when we consider $\alpha = 25\%$. Looking at Tables 11(a), 12(a) and 13(a), it is evident that the total cost increases by about 1% on average. The variation of the total costs is strongly related to the increase of the recharging costs respect to the model with partial recharging. In some cases, we observe an increase in the cost related to the use of regular vehicles in which we incur when we do not fully recharge, because the total recharging of the EV is more expensive (Figure 4.2). Figures 4.2 and 4.2 show how the full recharging affects not only the total cost, but also the solution's configuration. In particular Figure 4.2 represents the solutions obtained for the instance $C101C5\_0.25$ and Figure 4.2 those obtained for $R105C5\_0.25$. The impact of full recharge is evident for small instances, but is more interesting when the number of customers is higher. Taking into account the solutions of $R202C15\_0.50$ we have a percentage of variation of about 1% due not only to the increase of recharging cost, but also to that of conventional routing cost, while the cost of EVs routing decreases. It is clear that introducing partial battery recharging to the model is the most profitably strategy to reduce not only the cost, but also the total emissions, which in a green perspective is one of the most difficult challenge.

Table 11: Comparison with total recharging model for instances with five customers

(a) Results for instances with five customers and $\alpha = 0.25$

	Cost variation	CV cost variation	EV cost variation	Recharge cost variation
$C101C5\_0.25$	0.01	0.00	0.00	0.69
$C103C5\_0.25$	0.00	0.00	0.00	-
$C206C5\_0.25$	0.00	0.00	0.00	-
$C208C5\_0.25$	0.02	-	0.00	0.28
$R104C5\_0.25$	0.00	0.00	0.00	-
$R105C5\_0.25$	0.00	0.39	-0.27	-1.00
$R202C5\_0.25$	0.01	-	0.00	0.34
$R203C5\_0.25$	0.01	-	0.01	0.07
$RC105C5\_0.25$	0.02	-	0.00	4.14
$RC108C5\_0.25$	0.01	0.00	0.00	0.41
$RC204C5\_0.25$	0.00	-	0.00	0.01
$RC208C5\_0.25$	0.02	-	0.00	0.36

(b) Results for instances with five customers and $\alpha = 0.50$

	Cost variation	CV cost variation	EV cost variation	Recharge cost variation
$C101C5\_0.25$	0.00	0.00	-	-
$C103C5\_0.25$	0.00	0.00	-1.00	0.00
$C206C5\_0.25$	0.00	0.00	-	0.00
$C208C5\_0.25$	0.00	0.00	-	-
$R104C5\_0.25$	0.00	0.00	-	0.00
$R105C5\_0.25$	0.00	0.00	-	-
$R202C5\_0.25$	0.00	0.00	-	-
$R203C5\_0.25$	0.00	0.00	-	-
$RC105C5\_0.25$	0.01	0.00	0.00	0.42
$RC108C5\_0.25$	0.00	0.00	-	-
$RC204C5\_0.25$	0.01	0.00	0.00	1.18
$RC208C5\_0.25$	0.00	0.00	-	-

4.3 ILS parameters setting

The development of our algorithm requires the setting of only one parameter, that is the maximum number of iterations Δ. To select the best value for Δ, we have carried out computational experiments on small- and medium-size instances. We have considered four different values for Δ, that is $100, 150, 200, 250$, and we have investigated how these values influence the behaviour of the metaheuristic in terms of solution quality and computational effort.

Figure 4 shows the execution time, averaged over the α values (i.e. $\alpha = 0.25, 0.50, 0.75$)

Table 12: Comparison with total recharging model for instances with 10 customers

(a) Results for instances with 10 customers and $\alpha = 0.25$

	Cost variation	CV cost variation	EV cost variation	Recharge cost variation
$C101C10\_0.25$	0.02	0.00	0.00	0.60
$C104C10\_0.25$	0.01	-	0.00	0.20
$C202C10\_0.25$	0.00	0.00	0.00	0.00
$C205C10\_0.25$	0.02	0.00	0.00	0.69
$R102C10\_0.25$	0.00	0.00	0.00	-
$R103C10\_0.25$	0.00	-0.12	0.07	-
$R201C10\_0.25$	0.01	0.00	0.00	0.52
$R203C10\_0.25$	0.01	0.00	0.00	0.85
$RC102C10\_0.25$	0.02	0.00	0.01	0.81
$RC108C10\_0.25$	0.00	0.00	0.00	0.00
$RC201C10\_0.25$	0.02	-0.09	0.06	0.94
$RC205C10\_0.25$	0.00	0.00	-	-

(b) Results for instances with 10 customers and $\alpha = 0.50$

	Cost variation	CV cost variation	EV cost variation	Recharge cost variation
$C101C10\_0.50$	-0.01	-0.19	0.27	1.88
$C104C10\_0.50$	0.00	0.00	0.07	-
$C202C10\_0.50$	0.01	-0.01	0.02	2.55
$C205C10\_0.50$	0.00	0.00	-	-
$R102C10\_0.50$	0.00	0.00	-	-
$R103C10\_0.50$	0.00	0.00	-	-
$R201C10\_0.50$	0.00	0.31	-0.26	-1.00
$R203C10\_0.50$	0.00	0.00	-	-
$RC102C10\_0.50$	0.00	0.00	0.00	-
$RC108C10\_0.50$	0.00	0.00	-	-
$RC201C10\_0.50$	0.00	0.00	0.00	0.00
$RC205C10\_0.50$	0.00	0.00	-	-

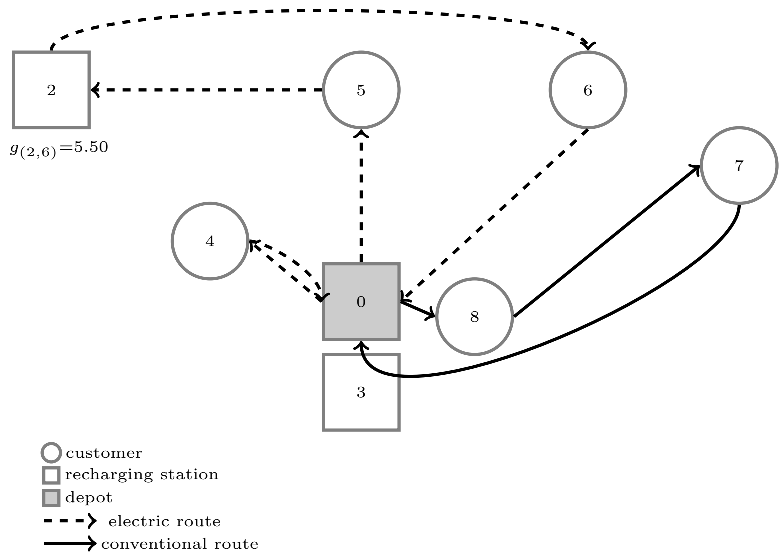
Table 13: Comparison with total recharging model for instances with 15 customers

(a) Results for instances with 15 customers and $\alpha = 0.25$

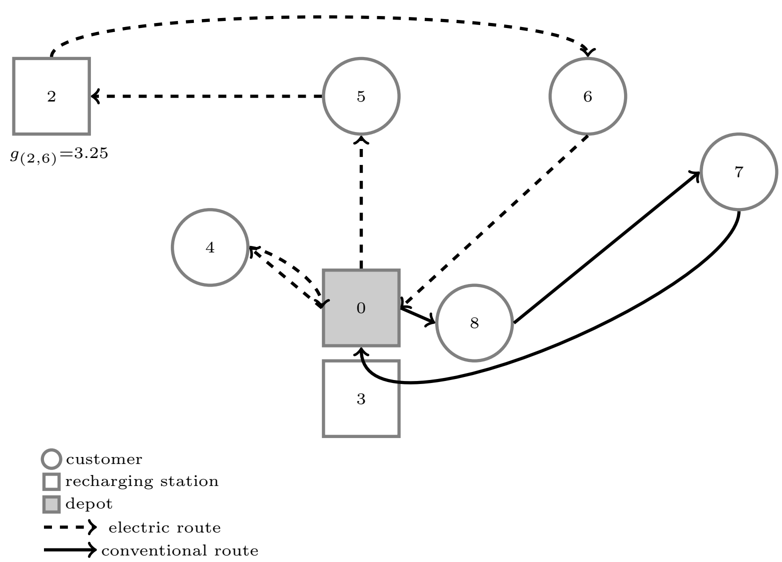
	Cost variation	CV cost variation	EV cost variation	Recharge cost variation
$C103C15\_0.25$	0.03	0.00	0.00	0.91
$C106C15\_0.25$	0.00	0.00	0.00	0.16
$C202C15\_0.25$	0.01	0.03	-0.01	0.43
$C208C15\_0.25$	0.01	0.00	0.00	0.21
$R202C15\_0.25$	0.00	0.00	0.00	-
$R209C15\_0.25$	0.02	0.11	0.00	2.23
$R102C15\_0.25$	0.02	0.00	0.00	0.60
$R105C15\_0.25$	0.01	0.00	0.00	0.17
$RC103C15\_0.25$	0.00	0.00	0.00	0.34
$RC108C15\_0.25$	0.00	0.67	-0.15	-0.61
$RC202C15\_0.25$	0.01	0.00	0.00	0.34
$RC204C15\_0.25$	0.01	0.00	0.00	0.30

(b) Results for instances with 15 customers and $\alpha = 0.50$

	Cost variation	CV cost variation	EV cost variation	Recharge cost variation
$C103C15\_0.50$	0.01	-0.05	0.13	3.78
$C106C15\_0.50$	0.00	0.00	-	-
$C202C15\_0.50$	0.01	0.00	0.01	0.37
$C208C15\_0.50$	0.00	0.00	0.00	-
$R102C15\_0.50$	0.00	0.04	-0.15	-
$R105C15\_0.50$	0.01	-0.04	0.11	3.00
$R202C15\_0.50$	0.01	0.45	-0.35	1.12
$R209C15\_0.50$	0.02	0.00	0.00	1.94
$RC103C15\_0.50$	0.00	0.00	-	-
$RC108C15\_0.50$	0.00	0.00	0.00	0.19
$RC202C15\_0.50$	0.00	0.00	0.00	-
$RC204C15\_0.50$	0.01	0.00	0.00	1.06



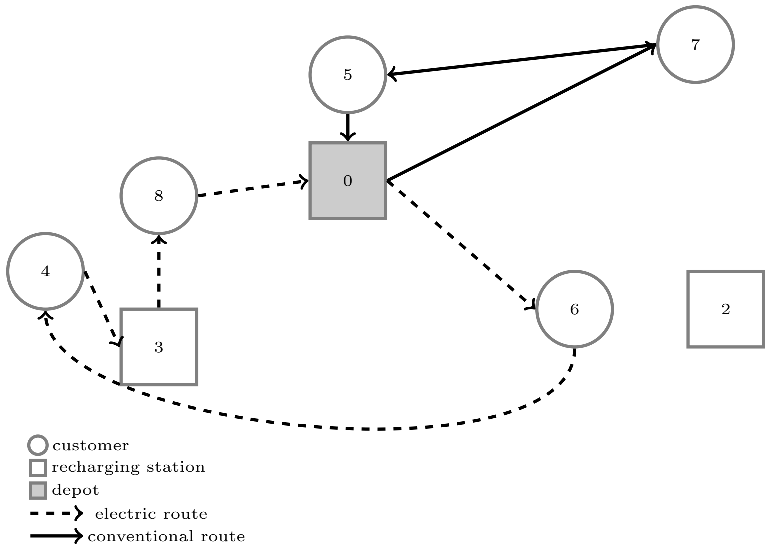
(c) Representation of the solution obtained for $C101C5\_0.25$ with full recharging model



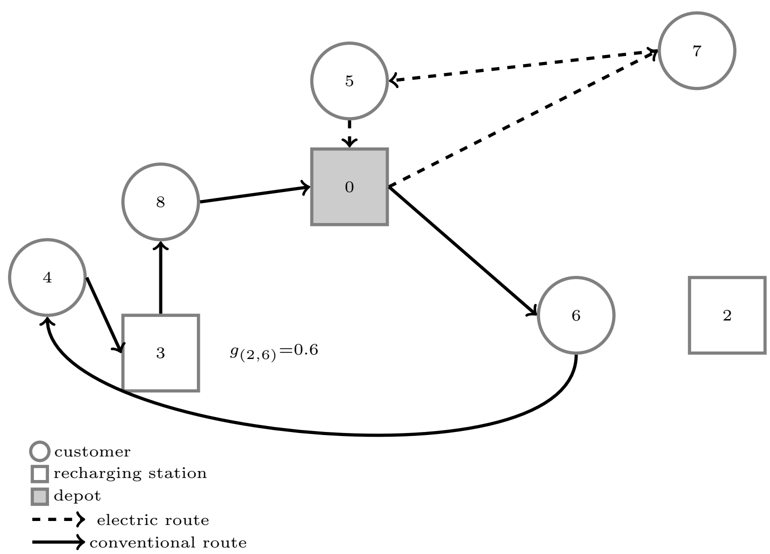
(d) Representation of the solution obtained for $C101C5\_0.25$ with partial recharging model

The solutions of the instance $C101C5\_0.25$ obtained by using the two models have the same paths and configurations. However, the full recharging is about the 70% higher than the partial one.

Figure 2: Representation of the solution obtained for $C101C5\_0.25$



(a) Representation of the solution obtained for $C101C5\_0.25$ with full recharging model



(b) Representation of the solution obtained for $C101C5\_0.25$ with partial recharging model

For the instance $R105C5\_0.25$, the solution obtained by using the model with full recharging scheme does not require any visit to the recharging station. The solution scheme is the same but the paths for conventional and EVs are inverted. Even if the solution cost is almost the same, the conventional vehicles routing cost increases by about 40% and the emissions are about 34.5% higher than those obtained by using our model.

Figure 3: Representation of the solution obtained for $R105C5\_0.25$

as a function of Δ on small-size instances. Figure 4 clearly highlights that after 200 iterations the execution time required by ILS sharply increases, in particular for instances with 15 customers. Since the influence of the value of Δ on the algorithm behaviour is more evident when the size of the instance increases, Table 14 shows the percentage cost variation, calculated as $100 \times (c_{\Delta_e} - c_{\Delta_s})/c_{\Delta_s}$, where c_{Δ_s} and c_{Δ_e} are the cost values obtained when Δ is set to Δ_s and Δ_e, respectively, for the instances with 15 customers. The results of Table 14 are averaged on the cost values obtained with $\alpha = 0.25, 0.50$, and 0.75.

Looking at Table 14, it is clear that after 200 iterations the cost reduction decreases, while the computational time rises considerably. The same trend was also observed for medium-size instances, as shown in Table 15, where the average percentage cost and time variations are given. Indeed, after 200 iterations the computational time continues to rise, while the cost reduction slows down. Since the main goal of the ILS is to find good quality solutions within a short computational time, we fixed the maximum number of iterations to 200, which yields the best trade-off between computational effort and solution quality.

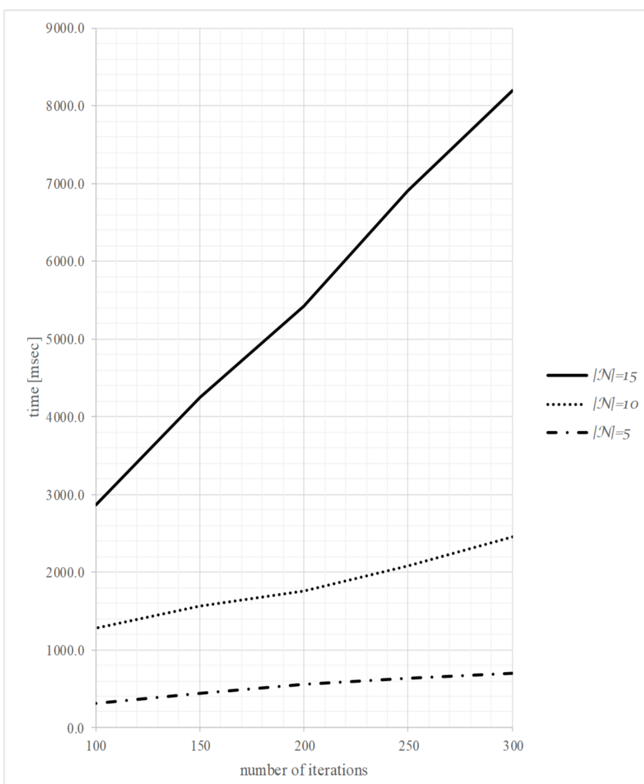


Figure 4: Time trend varying number of ILS iterations

Table 14: Cost variation for instances with $|\mathcal{N}|$=15

Δ_s	Δ_e	Cost variation
250	300	-0.12%
200	250	-0.20%
150	**200**	**-0.43%**
100	150	-0.45%

Table 15: Percentage cost and time variation for medium-size instances

		$\|\mathcal{N}\|$=20		$\|\mathcal{N}\|$=30	
Δ_s	Δ_e	Time variation	Cost variation	Time variation	Cost variation
250	300.00	17.30%	-0.08%	17.72%	-0.46%
200	250.00	21.57%	-0.25%	21.87%	-0.17%
150	**200.00**	43.30%	**-0.54%**	28.95%	**-0.94%**
100	150.00	49.38%	-0.92%	56.73%	0.18%

4.4 Numerical results

The computational study is divided into three phases. In the first phase, we analyze the impact of the model parameters values on optimal solutions in terms of cost and configuration (i.e. the number of EVs or conventional vehicles). In the second phase we compare the results obtained by using the proposed ILS with the optimal solution costs obtained with CPLEX. Since CPLEX was able to solve only the small-size instances, the first two phases are limited to the first set of instances. In the third phase we study the solutions obtained on instances with 25 customers or more and solved by ILS. In Section 4.2, we describe the computational results obtained by solving the model with CPLEX for small-size instances, varying several parameters. In Section 4.4.1, we focus on the results obtained on the first set of test instances i.e., the small-size ones. In Section 4.4.2, we test the heuristic on the medium- and large-size instances.

4.4.1 Numerical Results on the small-size test instances

To assess the performance of the ILS, we carried out a computational testing with the aim of comparing the quality of the solutions yielded by the proposed heuristic with those obtained by solving the model. We imposed a time limit of four hours on the execution time of the solver. We evaluated the performance of the proposed heuristic along two dimensions: solution quality and computational effort.

Table 16: Results for the instances with $\mid \mathcal{N} \mid$=5

(a) Results for instances with $\alpha = 0.25$

Test	ILS	
	g_c	Speedup
$C101C5\_0.25$	0.04%	1.81
$C103C5\_0.25$	0.00%	2.37
$C206C5\_0.25$	0.00%	3.03
$C208C5\_0.25$	11.63%	2.60
$R104C5\_0.25$	0.00%	1.77
$R105C5\_0.25$	0.25%	1.37
$R202C5\_0.25$	6.51%	1.76
$R203C5\_0.25$	1.97%	3.04
$RC105C5\_0.25$	0.04%	3.71
$RC108C5\_0.25$	4.01%	2.36
$RC204C5\_0.25$	1.26%	4.56
$RC208C5\_0.25$	3.85%	2.57
Average	2.46%	2.58

(b) Results for instances with $\alpha = 0.50$

Test	ILS	
	g_c	Speedup
$C101C5\_0.50$	2.29%	1.25
$C103C5\_0.50$	0.00%	2.58
$C206C5\_0.50$	0.00%	3.51
$C208C5\_0.50$	0.00%	1.97
$R104C5\_0.50$	0.00%	1.44
$R105C5\_0.50$	0.00%	1.45
$R202C5\_0.50$	0.00%	1.29
$R203C5\_0.50$	0.00%	3.23
$RC105C5\_0.50$	0.00%	5.35
$RC108C5\_0.50$	1.96%	3.07
$RC204C5\_0.50$	0.00%	3.30
$RC208C5\_0.50$	0.06%	3.45
Average	0.36%	2.66

(c) Results for instances with $\alpha = 0.75$

Test	ILS	
	g_c	Speedup
$C101C5\_0.75$	0.00%	1.95
$C103C5\_0.75$	0.21%	2.50
$C206C5\_0.75$	0.00%	2.49
$C208C5\_0.75$	0.00%	1.70
$R104C5\_0.75$	0.00%	1.42
$R105C5\_0.75$	0.00%	1.19
$R202C5\_0.75$	0.00%	1.23
$R203C5\_0.75$	0.00%	3.31
$RC105C5\_0.75$	0.00%	4.52
$RC108C5\_0.75$	0.00%	3.21
$RC204C5\_0.75$	0.00%	2.80
$RC208C5\_0.75$	0.00%	2.70
Average	0.02%	2.42

Table 17: Results for the instances with $|\mathcal{N}|$=10

(a) Results for instances with $\alpha = 0.25$

Test	ILS	
	g_c	Speedup
$C101C10\_0.25$	2.14%	4.28
$C104C10\_0.25$	13.93%	3.82
$C202C10\_0.25$	13.11%	3.69
$C205C10\_0.25$	14.84%	1.00
$R102C10\_0.25$	0.83%	6.30
$R103C10\_0.25$	0.00%	63.74
$R201C10\_0.25$	7.87%	2.73
$R203C10\_0.25$	1.19%	66.69
$RC102C10\_0.25$	0.60%	14.50
$RC108C10\_0.25$	0.00%	37.13
$RC201C10\_0.25$	0.89%	2.40
$RC205C10\_0.25$	0.00%	3.59
Average	4.62%	17.49

(b) Results for instances with $\alpha = 0.50$

Test	ILS	
	g_c	Speedup
$C101C10\_0.50$	0.03%	15.81
$C104C10\_0.50$	0.00%	5.33
$C202C10\_0.50$	4.34%	2.70
$C205C10\_0.50$	0.00%	2.48
$R102C10\_0.50$	0.00%	1.56
$R103C10\_0.50$	0.00%	6.05
$R201C10\_0.50$	0.06%	58.19
$R203C10\_0.50$	0.00%	2.65
$RC102C10\_0.50$	0.00%	14.18
$RC108C10\_0.50$	0.00%	3.66
$RC201C10\_0.50$	0.00%	11.85
$RC205C10\_0.50$	0.00%	1.55
Average	0.37%	10.50

(c) Results for instances with $\alpha = 0.75$

Test	ILS	
	g_c	Speedup
$C101C10\_0.75$	0.00%	3.25
$C104C10\_0.75$	0.00%	7.99
$C202C10\_0.25$	0.00%	2.95
$C205C10\_0.75$	0.00%	1.70
$R102C10\_0.75$	0.00%	2.18
$R103C10\_0.75$	0.00%	1.57
$R201C10\_0.75$	0.00%	5.74
$R203C10\_0.75$	0.00%	55.01
$RC102C10\_0.75$	0.00%	2.81
$RC108C10\_0.75$	0.00%	22.74
$RC201C10\_0.75$	0.00%	3.58
$RC205C10\_0.75$	0.00%	14.55
Average	0.00%	10.34

Table 18: Results for the instances with $\mid \mathcal{N} \mid$=15

(a) Results for instances with $\alpha = 0.25$

Test	ILS	
	g_c	Speedup
$C103C15\_0.25$	2.13%	297.74
$C106C15\_0.25$	0.00%	0.93
$C202C15\_0.25$	1.42%	92.64
$C208C15\_0.25$	0.00%	7.70
$R202C15\_0.25$	0.27%	264.20
$R209C15\_0.25$	0.00%	2.92
$R102C15\_0.25$	2.15%	931.21
$R105C15\_0.25$	2.27%	37.29
$RC103C15\_0.25$	0.53%	1607.65
$RC108C15\_0.25$	2.26%	17099.64
$RC202C15\_0.25$	0.00%	24.68
$RC204C15\_0.25$	0.00%	2381.20
Average	0.92%	1895.65

(b) Results for instances with $\alpha = 0.50$

Test	ILS	
	g_c	Speedup
$C103C15\_0.50$	0.48%	678.04
$C106C15\_0.50$	2.30%	3.01
$C202C15\_0.50$	1.21%	152.90
$C208C15\_0.50$	0.00%	11.51
$R202C15\_0.50$	0.27%	211.77
$R209C15\_0.50$	0.77%	3.01
$R102C15\_0.50$	2.54%	530.30
$R105C15\_0.50$	9.54%	66.75
$RC103C15\_0.50$	0.53%	760.08
$RC108C15\_0.50$	1.28%	17697.47
$RC202C15\_0.50$	2.58%	40.75
$RC204C15\_0.50$	1.83%	3056.36
Average	1.94%	1934.33

(c) Results for instances with $\alpha = 0.75$

Test	ILS	
	g_c	Speedup
$C103C15\_0.75$	2.13%	297.74
$C106C15\_0.75$	0.00%	0.93
$C202C15\_0.75$	1.42%	92.64
$C208C15\_0.75$	0.00%	7.70
$R102C15\_0.75$	0.27%	264.20
$R105C15\_0.75$	0.00%	2.92
$R202C15\_0.75$	2.15%	931.21
$R209C15\_0.75$	2.27%	37.29
$RC103C15\_0.75$	0.53%	1607.65
$RC108C15\_0.75$	2.26%	17099.64
$RC202C15\_0.75$	0.00%	24.68
$RC204C15\_0.75$	0.00%	2381.20
Average	0.92%	1895.65

Tables 16 to 18 present the related computational results. For each test instance, we report in the second column the percentage gap in cost g_c, defined as $g_c = (c^H - c^M)/c^M$, where c^H is the cost provided by the heuristic and c^M is the cost obtained solving the model. In the third column we report the speedup value i.e. the ratio between the computational time required by CPLEX and that of the heuristic.

The computational results clearly demonstrate the advantage of the proposed heuristic in terms of efficiency. This advantage becomes more evident on large instances. Indeed, the larger the number of the customers, the higher the speedup value achieved. In particular, the ILS is on average 2.55 times faster on the set with five customers, and up to 1908.54 time faster on the set with 15 customers. The ILS overall outperforms in terms of efficiency CPLEX.

It is worth observing that the heuristic is also effective. Looking at Tables 16(a) to 16(c), it is clear that the ILS is more effective when α is equal to 0.50 and 0.75. Indeed, it finds an optimal solution for the majority of the instances. However, the average on the cost gap is less than 1% for both the sets, while it increases to 2.46% for $\alpha = 0.25\%$. The results in Tables 17(a) to 17(c) and 18(a) to 18(c) exhibit the same trend. Indeed, when α = 0.75, the ILS finds optimal solutions for all the instances with 10 customers (see Table 17(c)), and the average on the cost gap is less than 1% for the instances with 15 customers (see Table 18(c)). When $\alpha = 0.50$, the average on gap is 0.37% and 1.94% for the instances with 10 and 15 customers, respectively. Table 19 summarizes the percentage deviations of the solution costs found by the ILS from the optimal solution values and the values of speedup values with varying values of α. The table clearly shows the efficiency of the proposed algorithm for all sets of instances. The parameter α has a significant impact on the quality of the solution found by the ILS. The best setting is obtained with $\alpha = 0.75$, but the average on percentage gap is less than 2%.

It is interesting to observe how the ILS performs better on short scheduling horizons, in terms of optimality gap and speedup. Looking at results summarized in Table 20, it is clear that the ILS is high competitive in terms of speedup when instances with short scheduling horizon are considered. On average the speedup is about 1077, while for instances with long scheduling it is about 205.5. Even if the ILS finds good solutions for both classes, the optimality gap is on average less than 1% for the instances with a short scheduling horizon, and about 2% for instances with a long scheduling horizon.

4.4.2 Numerical Results on the medium-size and large-size test instances

In this section we describe the results obtained for the instances with more than 25 customers, for detailed results the reader is referred to Appendix 7. Tables 23 to 26 show the results obtained for the medium- and large-size instances. In particular, for each table, the

Table 19: Average Speedup and percentage deviations of the solution costs found by the ILS from the optimal solution values with varying α

Test		ILS g_c	ILS Speedup
$\mid \mathcal{N} \mid=5$	$\alpha = 0.25$	2.46%	2.58
	$\alpha = 0.50$	0.36%	2.66
	$\alpha = 0.75$	0.02%	2.42
Average		0.95%	2.55
$\mid \mathcal{N} \mid=10$	$\alpha = 0.25$	4.62%	17.49
	$\alpha = 0.50$	0.37%	10.50
	$\alpha = 0.75$	0.00%	10.34
Average		1.66%	12.78
$\mid \mathcal{N} \mid=15$	$\alpha = 0.25$	0.92%	1895.65
	$\alpha = 0.50$	1.94%	1934.33
	$\alpha = 0.75$	0.92%	1895.65
Average		1.26%	1908.54

first column displays the name of the instance, while the others give the time in seconds and the cost obtained by the ILS. Table 21 summarizes the average time required by the ILS to solve the instances. Overall, the ILS finds the solutions within short computation times. Indeed, the ILS solves all instances with 25 and 30 customers within less than 20 seconds, while the instances with 50 customers are solved within less than two minutes, and the large-size instances within about 11 minutes. Looking at the results, it is possible to conclude that the ILS is less time consuming when α is set equal to 0.50 or 0.75. From Tables 23 to 26 it is evident that the lower the value of α, the higher the average solution cost. This specific behaviour can be explained by observing that when the emissions constraints are tighter, more EVs are used since only a limited number of ICCVs can be considered. Table 22 shows the percentage of impact of the EVs use on the total costs. When $\alpha = 0.25$, the number of routed EVs increases and the cost associated with these vehicles is higher than the cost of the conventional ones, in particular, it is more than 90% for all the classes.

Table 20: Summary of ILS average performance for short and long scheduling horizon small-size instances

Test		$\alpha_s = 0.25$		$\alpha_s = 0.50$		$\alpha_s = 0.75$	
		g_c	Speedup	g_c	Speedup	g_c	Speedup
Short	$\mid\mathcal{N}\mid$=5	0.72%	2.23	0.71%	2.52	0.04%	2.47
scheduling	$\mid\mathcal{N}\mid$=10	2.92%	21.63	0.00%	7.76	0.00%	6.76
horizon	$\mid\mathcal{N}\mid$=15	0.87%	3212.18	0.94%	3225.56	0.87%	3212.18
Average		1.50%	1078.68	0.55%	1078.62	0.30%	1073.80
Long	$\mid\mathcal{N}\mid$=5	4.20%	2.93	0.01%	2.79	0.00%	2.37
scheduling	$\mid\mathcal{N}\mid$=10	6.32%	13.35	0.73%	13.24	0.00%	13.92
horizon	$\mid\mathcal{N}\mid$=15	0.97%	579.12	2.95%	643.09	0.97%	579.12
Average		3.83%	198.47	1.23%	219.71	0.32%	198.47

Table 21: Summary of ILS averages time execution [seconds] for the medium- and large-size instances

Test		Time	Test		Time
	$\alpha = 0.25$	22.89		$\alpha = 0.25$	135.29
$\mid\mathcal{N}\mid$=25	$\alpha = 0.50$	11.45	$\mid\mathcal{N}\mid$=50	$\alpha = 0.50$	126.04
	$\alpha = 0.75$	14.06		$\alpha = 0.75$	117.09
Average		16.13	Average		126.14
	$\alpha = 0.25$	22.52		$\alpha = 0.25$	679.97
$\mid\mathcal{N}\mid$=30	$\alpha = 0.50$	20.03	$\mid\mathcal{N}\mid$=100	$\alpha = 0.50$	669.98
	$\alpha = 0.75$	18.37		$\alpha = 0.75$	647.97
Average		20.31	Average		665.97

5 Conclusions

We have introduced, modelled and solved the green mixed fleet vehicle routing problem with partial battery recharging and time windows. We have proposed a mathematical model and an iterated local search metaheuristic to solve it. We have conducted several computational experiments on modified benchmark instances in order to analyse the influence of the main features of the problem (i.e. time windows, pollution emissions and partial recharging) on solution configuration and costs, and to evaluate the behaviour of the proposed heuristic. Our test results have shown on one hand that the planning horizon length and the upper bounds on pollution emission influence the cost and configuration of the solutions, on the other hand that the use of partial recharge may lead to more effective

Table 22: Electric Vehicle impact cost

$\mid \mathcal{N} \mid$	$\alpha = 0.25$	$\alpha = 0.50$	$\alpha = 0.75$
25	93%	69%	27%
30	92%	70%	34%
50	94%	87%	82%
100	96%	91%	87%

and sustainable solutions. The results have also shown that the developed method can find good quality solutions within a reasonable amount of time.

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7 Appendix

Table 23: Results for the instances with $|\mathcal{N}|$=25

Instance	ILS Time [s]	ILS Cost	Instance	ILS Time [s]	ILS Cost	Instance	ILS Time [s]	ILS Cost
C101C25_0.25	23.18	276.00	C101C25_0.50	11.42	256.00	C101C25_0.75	13.94	245.00
C102C25_0.25	22.54	233.00	C102C25_0.50	11.98	244.00	C102C25_0.75	15.38	227.00
C103C25_0.25	20.76	233.00	C103C25_0.50	12.80	225.00	C103C25_0.75	16.30	210.00
C104C25_0.25	22.07	225.00	C104C25_0.50	14.23	219.00	$C104C25$_0.75	16.56	208.00
C105C25_0.25	19.48	262.00	C105C25_0.50	12.19	259.00	C105C25_0.75	14.72	250.00
R101C25_0.25	19.84	575.00	R101C25_0.50	10.41	571.00	R101C25_0.75	13.30	570.00
R102C25_0.25	20.33	502.00	R102C25_0.50	10.97	501.00	R102C25_0.75	13.83	500.00
R103C25_0.25	21.43	431.00	R103C25_0.50	11.36	431.00	R103C25_0.75	14.50	426.00
R104C25_0.25	22.95	407.00	R104C25_0.50	12.53	410.00	R104C25_0.75	14.70	401.00
R105C25_0.25	20.83	494.00	R105C25_0.50	11.34	493.00	R105C25_0.75	13.41	494.00
RC101C25_0.25	24.07	472.00	RC101C25_0.50	9.84	473.00	RC101C25_0.75	12.27	470.00
RC102C25_0.25	26.27	392.00	RC102C25_0.50	10.95	382.00	RC102C25_0.75	13.03	380.00
RC103C25_0.25	27.25	310.00	RC103C25_0.50	10.25	311.00	RC103C25_0.75	13.27	309.00
RC104C25_0.25	27.38	371.00	RC104C25_0.50	11.28	306.00	RC104C25_0.75	14.20	309.00
RC105C25_0.25	24.93	453.00	RC105C25_0.50	10.25	450.00	RC105C25_0.75	12.19	453.00
Average	22.89	379.92	Average	11.45	372.23	Average	14.06	367.23

Table 24: Results for the instances with $|\mathcal{N}|$=30

Instance	ILS Time [s]	ILS Cost	Instance	ILS Time [s]	ILS Cost	Instance	ILS Time [s]	ILS Cost
C101C30_0.25	23.53	280.00	C101C30_0.50	14.48	281.00	C101C30_0.75	13.39	266.00
C102C30_0.25	17.45	259.00	C102C30_0.50	15.36	267.00	C102C30_0.75	13.94	277.00
C103C30_0.25	18.42	274.00	C103C30_0.50	16.13	269.00	C103C30_0.75	14.88	253.00
C104C30_0.25	22.05	238.00	C104C30_0.50	18.09	241.00	C104C30_0.75	16.36	217.00
C105C30_0.25	15.66	278.00	C105C30_0.50	14.86	283.00	C105C30_0.75	13.61	271.00
R101C30_0.25	16.63	660.00	R101C30_0.50	15.19	655.00	R101C30_0.75	13.73	648.00
R102C30_0.25	18.11	576.00	R102C30_0.50	16.59	569.00	R102C30_0.75	15.44	567.00
R103C30_0.25	19.97	464.00	R103C30_0.50	17.75	456.00	R103C30_0.75	16.03	457.00
R104C30_0.25	21.75	434.00	R104C30_0.50	19.52	412.00	R104C30_0.75	17.69	415.00
R105C30_0.25	19.05	532.00	R105C30_0.50	17.67	533.00	R105C30_0.75	15.80	530.00
RC101C30_0.25	26.50	673.00	RC101C30_0.50	24.97	616.00	RC101C30_0.75	22.88	659.00
RC102C30_0.25	28.86	554.00	RC102C30_0.50	26.67	570.00	RC102C30_0.75	24.73	520.00
RC103C30_0.25	30.45	556.00	RC103C30_0.50	27.78	519.00	RC103C30_0.75	25.78	515.00
RC104C30_0.25	31.44	434.00	RC104C30_0.50	29.58	441.00	RC104C30_0.75	27.44	437.00
RC105C30_0.25	27.95	587.00	RC105C30_0.50	25.86	580.00	RC105C30_0.75	23.91	562.00
Average	22.52	453.27	Average	20.03	446.13	Average	18.37	439.60

Table 25: Results for the instances with $| \mathcal{N} |$=50

Instance	ILS		Instance	ILS		Instance	ILS	
	Time [s]	Cost		Time [s]	Cost		Time [s]	Cost
C101C50_0.25	106.36	280.00	C101C50_0.50	99.40	281.00	C101C50_0.75	91.68	266.00
C102C50_0.25	124.21	259.00	C102C50_0.50	118.78	267.00	C102C50_0.75	110.03	277.00
C103C50_0.25	141.17	274.00	C103C50_0.50	135.24	269.00	C103C50_0.75	121.43	253.00
C104C50_0.25	154.66	238.00	C104C50_0.50	148.11	241.00	C104C50_0.75	136.05	217.00
C105C50_0.25	112.60	278.00	C105C50_0.50	105.58	283.00	C105C50_0.75	101.45	271.00
R101C50_0.25	91.70	660.00	R101C50_0.50	85.50	655.00	R101C50_0.75	79.67	648.00
R102C50_0.25	100.03	576.00	R102C50_0.50	93.57	569.00	R102C50_0.75	87.50	567.00
R103C50_0.25	118.16	464.00	R103C50_0.50	111.92	456.00	R103C50_0.75	102.21	457.00
R104C50_0.25	125.72	434.00	R104C50_0.50	116.50	412.00	R104C50_0.75	111.31	415.00
R105C50_0.25	107.05	532.00	R105C50_0.50	100.92	533.00	R105C50_0.75	94.86	530.00
RC101C50_0.25	150.71	673.00	RC101C50_0.50	137.31	616.00	RC101C50_0.75	130.42	659.00
RC102C50_0.25	164.07	554.00	RC102C50_0.50	152.90	570.00	RC102C50_0.75	140.48	520.00
RC103C50_0.25	180.62	556.00	RC103C50_0.50	163.60	519.00	RC103C50_0.75	153.66	515.00
RC104C50_0.25	189.57	434.00	RC104C50_0.50	173.25	441.00	RC104C50_0.75	159.48	437.00
RC105C50_0.25	162.69	587.00	RC105C50_0.50	147.95	580.00	RC105C50_0.75	136.14	562.00
Average	135.29	453.27	Average	126.04	446.13	Average	117.09	439.60

Table 26: Results for the instances with $| \mathcal{N} |$=100

Instance	ILS		Instance	ILS		Instance	ILS	
	Time [s]	Cost		Time [s]	Cost		Time [s]	Cost
C101_0.25	814.25	280.00	C101_0.50	770.15	281.00	C101_0.75	768.76	266.00
C102_0.25	852.94	259.00	C102_0.50	841.27	267.00	C102_0.75	826.15	277.00
C103_0.25	994.01	274.00	C103_0.50	922.22	269.00	C103_0.75	918.57	253.00
C104_0.25	1033.26	238.00	C104_0.50	1004.99	241.00	C104_0.75	963.90	217.00
C105_0.25	862.44	278.00	C105_0.50	841.44	283.00	C105_0.75	799.58	271.00
R101_0.25	392.67	660.00	R101_0.50	363.78	655.00	R101_0.75	357.99	648.00
R102_0.25	392.98	576.00	R102_0.50	397.04	569.00	R102_0.75	388.05	567.00
R103_0.25	532.67	464.00	R103_0.50	507.95	456.00	R103_0.75	477.32	457.00
R104_0.25	589.78	434.00	R104_0.50	543.32	412.00	R104_0.75	515.88	415.00
R105_0.25	521.50	532.00	R105_0.50	414.59	533.00	R105_0.75	456.61	530.00
RC101_0.25	527.03	673.00	RC101_0.50	506.63	616.00	RC101_0.75	508.92	659.00
RC102_0.25	546.05	554.00	RC102_0.50	699.91	570.00	RC102_0.75	655.11	520.00
RC103_0.25	781.71	556.00	RC103_0.50	753.17	519.00	RC103_0.75	691.04	515.00
RC104_0.25	840.80	434.00	RC104_0.50	786.31	441.00	RC104_0.75	735.89	437.00
RC105_0.25	517.44	587.00	RC105_0.50	697.01	580.00	RC105_0.75	655.84	562.00
Average	679.97	453.27	Average	669.98	446.13	Average	647.97	439.60

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