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J. Puchinger, M. Schiffer, T. Vidal

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# Sustainable city logistics via access restrictions? An impact assessment of city center policies

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**Abstract:** Cities are facing severe traffic-related problems causing emission thresholds to be exceeded. All around the world, city center access restriction policies are being tested to foster the adoption of electric commercial vehicles (ECVs) and to reduce emissions. In this paper, we analyze the impact of a broad spectrum of such policies on fleet logistics. We develop an algorithm that solves large real-world instances and mimics a fleet operator’s decisions. We present a multigraph setting to handle trade-offs between cheapest and quickest paths. Further, we consider the cost structure of heterogeneous fleets. Our results provide the basis for municipalities to use decision support to identify suitable city center access restriction policies. We show which pricing schemes and restriction policies encourage the sustainable usage of ECVs in logistics fleets. We further show which policies have a negative impact on fleet operations, e.g., by increasing the traveled distance or emissions.

**Keywords:** City center access restrictions, urban freight transport, sustainable logistics

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# 1 Introduction

It is challenging to preserve quality of life and infrastructure service levels in cities, mainly because of two reinforcing trends. First, urbanization is soaring worldwide. Currently, 55% of the world's population lives in urban areas, and experts envision an increase to 68% by 2050. Second, the rapid growth of e-commerce has led to increased delivery volumes in city centers, and a 300% increase in demand for urban freight transportation is likely by 2050 (Van Aудenhove et al., 2015). Both trends increase traffic, pollution (CO<sub>2</sub>, NO<sub>x</sub>, particulate matter), and noise. In the United States and the European Union, transportation is one of a few economic sectors for which the relative emission share is steadily increasing (European Commission, 2014; EPA, 2018).

Cities and their mobility systems have transformed rapidly in the past 150 years as a result of technological developments and political decisions (Gilbert and Pearl, 2012). In recent years, this transformation has slowed down significantly because the transportation infrastructure is in place, most transport modes are already exploited, and further spatial expansion is limited. New developments therefore focus on improving existing systems, e.g., giving incentives to ride sharing, or shifting demand peaks by encouraging flexible work hours (Jones, 2014). These changes have successfully improved passenger transportation but not freight transportation (Nuzzolo et al., 2016). For large volumes, there is often no alternative to road transportation, and vehicle load factors are already very high. Moreover, freight transportation is competitive, and no public authority exists to promote alternative, subsidized transport modes.

Consequently, the deployment of sustainable drive trains is one of the best options to reduce (local) emissions in city logistics. Governments originally attempted to stimulate the adoption of [electric commercial vehicles \(ECVs\)](#) by setting quotas or offering subsidies (e.g., tax credits). When these incentives turned out to be rather ineffective, some authorities (e.g., in Singapore, London, and Stockholm) started to promote [ECVs](#) by imposing time-, distance-, or entry-based fees for [internal combustion engine vehicles \(ICEVs\)](#) in city centers (Pike, 2010). Currently more cities are planning to impose such regulations (Garfield, 2018) but there exists no consensus which type of regulation creates the desired effect. Despite some recent work which based on simple geometries and continuous approximation approaches (Davis and Figliozzi, 2013; Franceschetti et al., 2017; Zhang et al., 2019), neither theoretical nor experimental assessment is available to support policy makers in their choice of a traffic-pricing paradigm for mixed fleets of electric and conventional vehicles. The objective of this paper is to close this important methodological gap.

## 1.1 Challenges and status quo

Municipalities and [logistic service providers \(LSPs\)](#) shape the landscape of city logistics. They share a common interest in preserving a reliable and stable logistics system, but their general objectives are conflicting.

**LSPs** aim to maximize their profit and market share by providing reliable B2B or B2C services. Service requirements (e.g., same-day or within two-hour deliveries) are steadily increasing while profit margins are decreasing. Moreover, new players are entering the market: major retailers are launching their own fleets (Amazon, 2018) and several crowdsourced courier services have emerged (GoPeople, 2015). Consequently, [LSPs](#) require cost-effective, volume-based operations to remain competitive, which often prevents a shift to sustainable transport modes.

**Municipalities** aim to preserve infrastructure services, accessibility, and quality of life in cities in the most sustainable way, e.g., by promoting measures that reduce emissions, traffic, and noise. In general, municipalities try to influence [LSPs'](#) behavior in city logistics via subsidies, taxes, or restrictions.

**ECV field projects** have been launched by some [LSPs](#) in recent years. The Deutsche Post DHL Group and United Parcel Services have launched short-haul logistics fleets (DPDHL, 2014; UPS, 2013) while others use [ECVs](#) in mid-haul logistics (Stütz et al., 2016). However, since [LSPs](#)

focus on cost, most fleets still consist of **ICEVs** because **ECVs** are generally less flexible and more expensive.

**City center access restrictions** have recently been established by municipalities in major cities to financially motivate **LSPs** to deploy **ECVs**. In general, these restrictions involve a fee for **ICEVs** that enter the city center.

Table 1 lists the main access restrictions applied in different cities. These policies differ significantly in terms of what is penalized (e.g., distance or time) and the fee type (event-based or volume-based). So far only limited evidence has been gathered on the benefits of each policy. Municipalities can use socioeconomic analysis (Nuzzolo et al., 2016) and simulation studies (Jlassi et al., 2018) to model the impact of these policies for point-to-point itineraries in passenger transportation, but they often lack the evaluation tools to study their impact on optimized logistics operations. To this end, an accurate evaluation tool is imperative because badly designed access policies and fees could trigger inverse effects, resulting in large detours and increased congestion.

**Table 1: Possible city center access fees and restrictions.**

F1) Daily fee (London, 2019; Milan, 2019; Durham, 2019)	<b>ICEVs</b> pay a fixed fee once a day when they enter the city center. Currently applied in London, Milan, and Durham.
F2) Entry fee (Sweden, 2019)	<b>ICEVs</b> pay a fixed fee each time they enter the city center. Currently applied in Stockholm and Gothenburg.
F3) Distance fee (Singapore, 2016, 2019)	<b>ICEVs</b> pay a fee proportional to the distance driven in the city center. Currently applied in Singapore, where the distance driven is approximated by gantries. A satellite-based system will be launched in 2020 to better track the distances.
F4) Time fee (Malta, 2019)	<b>ICEVs</b> pay a fixed fee that depends on the time spent in the city center. Currently applied in Valetta.
F5) <b>ICEV</b> ban (Garfield, 2018)	<b>ICEVs</b> are banned from the city center. Several cities in Europe have discussed or implemented this policy.

We therefore introduce an algorithmic framework for fleet composition and routing in the presence of city center access restrictions that mimics an **LSP**'s decisions. We use this tool to evaluate the impact of various restrictions and pricing schemes on fleet investment and operations. This modeling and evaluation framework will help transport operators to optimize their fleet composition and routes, and it will assist policymakers to evaluate the effects of new regulations.

## 1.2 State of the art

Our work is connected to two general research streams: **vehicle routing problems (VRPs)** with electric vehicles, and studies of congestion pricing.

Research on **VRPs** with electric vehicles has grown significantly in recent years. Early publications considered the recharging of **ECVs** at customers (Conrad and Figliozzi, 2011) or at dedicated charging stations (Schneider et al., 2014). Later work considered finer-grained operational characteristics, e.g., partial recharging (Keskin and Çatay, 2016), mixed fleets of **ICEVs** and **ECVs** (Goeke and Schneider, 2015; Hiermann et al., 2016, 2019), multiple echelons (Breunig et al., 2019), and exact solution approaches (Desaulniers et al., 2016). Other studies levied these models to a location-routing perspective, integrating charging-station location decision (Yang and Sun, 2015; Schiffer and Walther, 2017, 2018) or combined freight and charging facilities (Schiffer et al., 2018). While most of these studies focus on algorithmic contributions and artificial instance sets, some papers analyze the competitiveness of **ECVs** through **total cost of ownership (TCO)** analysis (Lee et al., 2013; Feng and Figliozzi, 2013; Davis and Figliozzi, 2013; Taefi, 2016) and approximate their operations to assess the routing costs. The only study that integrates a **TCO** perspective with strategic network design and operational routing decisions focuses on the electrification of a mid-haul retail logistics network (Schiffer et al., 2017). For more detailed discussions on related works, we refer to the recent surveys of Pelletier et al. (2016); Schiffer et al. (2019) and Vidal et al. (2019). In summary, studies of routing problems with **ECVs** remain

essentially focused on new problem variants and algorithmic contributions, whereas economic analyses are rather scarcer and typically built on simplistic models that ignore real operational constraints.

In contrast, most work on congestion pricing focuses on case studies and models agent or traffic behavior via discrete-time choice models (Olszewski and Xie, 2005), logit models (Eliasson et al., 2013), system dynamics (Sabounchi et al., 2014), or macroscopic traffic simulations (Wu et al., 2017). Further, work on congestion pricing design often focuses on equilibrium models (Ho et al., 2005) or game theoretic approaches (Jahn et al., 2005). Most of these models, however, focus on point-to-point transportation rather than optimized delivery tours for logistics fleets (Tsekeris and Voß, 2009). In the context of road pricing for logistics fleets, some papers present empirical studies (Holguín-Veras, 2011) or aggregated models (Zhang and Yang, 2004). There are only a few publications in the field of vehicle routing: Quak and de Koster (2009) presented case studies that showed the environmental impact of regulation-based vehicle restrictions, while Wen and Eglese (2015) focused on a [VRP](#) with congestion charges, and Reinhardt et al. (2016) accounted for edge set costs to model highway charges.

In summary, [VRPs](#) that consider [ECV](#) constraints currently do not consider congestion pricing, and the few [VRP](#) approaches that consider congestion pricing for logistics fleets neglect the characteristics of [ECVs](#). Accordingly, there is no methodology to analyze the impact of different city center access restriction policies on the daily operations and fleet mixes of [LSPs](#).

### 1.3 Aims and scope

This paper closes some of the research gaps outlined above. We provide decision-making support for the design of restricted access zones in city centers, analyzing its impact on urban goods distribution with mixed fleets of conventional and electric vehicles. To this end, we analyze the point of view of [LSPs](#) and how they would adapt to access restrictions. Specifically, our contribution is threefold.

1. We introduce a solution algorithm that mimics the behavior of [LSPs](#) in the presence of city-center access restrictions. Besides providing general state-of-the-art results for heterogeneous fleet routing with electric vehicles, this algorithm can deal with a large variety of cost structures and access restrictions. It jointly optimizes fleet composition, customer-to-vehicle assignments, customer-visit sequences, and path choices between successive visits, which are nontrivial because of the numerous non-dominated trade-offs between time, distance, and congestion fees.
2. We perform real-world case studies for New York, Paris, and Vienna, which differ in terms of size and road network structure. Based on these cases, we conduct an extensive numerical study to evaluate access restrictions and pricing schemes, measuring the impact on pollution emissions and traffic flows. We show which pricing schemes and restriction policies encourage [ECV](#) usage and which policies have undesired effects, e.g., higher distances traveled or higher emissions.
3. We provide sensitivity analyses to generalize our findings. Specifically, we evaluate the impact of restricted area design (e.g., size) and characteristics of the logistics operations (e.g., time windows for customer deliveries and route length) on the effectiveness of the restriction policies.

Overall, the resulting algorithm and analyses can serve as a guide for municipalities and as a useful fleet-composition optimization tool for logistics companies.

### 1.4 Organization of the paper

The remainder of this paper is organized as follows. Section 2 introduces the methodological background for our studies, including a problem description and the proposed algorithmic framework. Section 3 details our case studies and experimental design. We discuss results in Section 4. Section 5 presents our managerial insights and conclusions.

## 2 Methodology

We want to evaluate the impact of different city center access restriction policies on an LSP's behavior in terms of fleet composition and daily operational decisions. Accordingly, we need a realistic estimate of an LSP's reaction to a certain policy. We take the viewpoint of an operator adapting its fleet composition under new access restriction policies. LSPs typically rely on heuristic optimization tools for daily planning and make fleet-composition decisions based on cost.

Thus, we derive a state-of-the-art metaheuristic for the fleet composition and routing problem under a city center access restriction policy. We allow mixed fleets of ICEVs and ECVs for three main reasons. First, evaluating only ICEVs would yield infeasible solutions for some scenarios and makes a comparison with ECVs impossible; second, a fleet operator is unlikely to replace its entire fleet at the same time; third, optimized heterogeneous fleets are often more cost-effective because they combine the advantages of different vehicle types (Hiermann et al., 2019). We therefore define and solve a vehicle fleet mix and routing problem (Vidal et al., 2013; Koç et al., 2016; Vidal et al., 2019) with conventional and electric vehicles, parametrized by fees and/or restrictions for city-center access. The remainder of this section formally describes our model, its reformulation based on a multigraph as well as our solution method.

### 2.1 The fleet mix and routing problem

In the following, we formally introduce the fleet mix and routing problem studied in this paper. We first focus on the graph reformulation of a city logistics system and general notation. We then detail feasibility constraints, city center access restriction policies, and the problem's objective.

#### Multigraph reformulation and solution representation

We focus on an LSP who operates a logistics fleet in a city logistics network. Such a network can be described by a graph  $\mathcal{G} = (\mathcal{V}, \mathcal{A})$ , with a set of vertices  $\mathcal{V}$  and a set of arcs  $\mathcal{A}$ . Vertices  $v \in \mathcal{V}$  represent the fleet's start depot, customer locations, recharging vertices, or crossroads in the underlying road network (cf. Figure 1a). Arcs  $(i, j) \in \mathcal{A}$  denote road segments, thus reflect the contentedness of the road network. Clearly, multiple paths exist between any two locations in this network and may differ in terms of driving distance, driving time, and cost.

To reduce the computational complexity while preserving the general trade-off between choosing a distance, time, or cost shortest paths, we transform the original graph  $\mathcal{G}$  (Figure 1a) into a multigraph  $\mathcal{G}' = (\mathcal{V}', \mathcal{A}')$  (Figure 1b), which does no longer contain crossroad vertices but multiple arcs between any two vertices  $i, j$  to model the option of choosing different paths to travel from  $i$  to  $j$ .

This new set of vertices  $\mathcal{V}'$  contains only vertices relevant to our problem and can be split into mutually exclusive subsets that contain either customer locations  $\mathcal{C}$ , recharging locations  $\mathcal{R}$ , or the central depot  $\{0\}$ , such that  $\mathcal{V}' = \{0\} \cup \mathcal{C} \cup \mathcal{R}$ . Each customer  $i \in \mathcal{C}$  has a freight demand  $d_i$ , a service time  $s_i$  that it takes to unload the freight after arriving at the customer, and a time window  $[e_i, l_i]$  within which the vehicle must deliver the freight to the customer. A time window at the depot determines the planning horizon.

We define  $\mathcal{A}' = \{(i, j, k, l) : i, j \in \mathcal{V}, k \in \mathcal{K}, l \in 1, \dots, h(i, j, k)\}$ , where  $h(i, j, k)$  is the number of arcs representing different nondominated paths in terms of time  $t_{ijl}^k$  and cost  $c_{ijl}^k$  from vertex  $v_i$  to  $v_j$  for a vehicle type  $k$ . We calculate this multiarc set in a preprocessing step for all pairs of vertices and use a sampling approach which generates up to  $\lambda + 1$  nondominated paths. This approach consists in finding, for each vehicle type  $k \in \mathcal{K}$ , the shortest paths with arc costs defined as  $x \cdot c_{ij}^k + (1 - x) \cdot t_{ij}^k$ , for  $x \in \{0, \frac{1}{\lambda}, \frac{2}{\lambda}, \dots, 1\}$ , where  $c_{ij}^k$  and  $t_{ij}^k$  represent the driving cost and time between nodes  $i$  and  $j$ . This is done efficiently by solving  $\lambda + 1$  all-pairs shortest path problems with the Floyd–Warshall algorithm (Floyd, 1962). We use  $\lambda = 10$  in our experiments to obtain a diverse set of paths.

The LSP can use vehicles of different types to operate her fleet. To differ between these types, we introduce the set  $\mathcal{K}$ , which consists of labels  $k \in \mathcal{K}$  for each vehicle type. In our specific case, the LSP may use ICEVs ( $\mathcal{K}^I$ ) and ECVs ( $\mathcal{K}^B$ ), such that  $\mathcal{K} = \mathcal{K}^I \cup \mathcal{K}^B$ . Characteristics of different



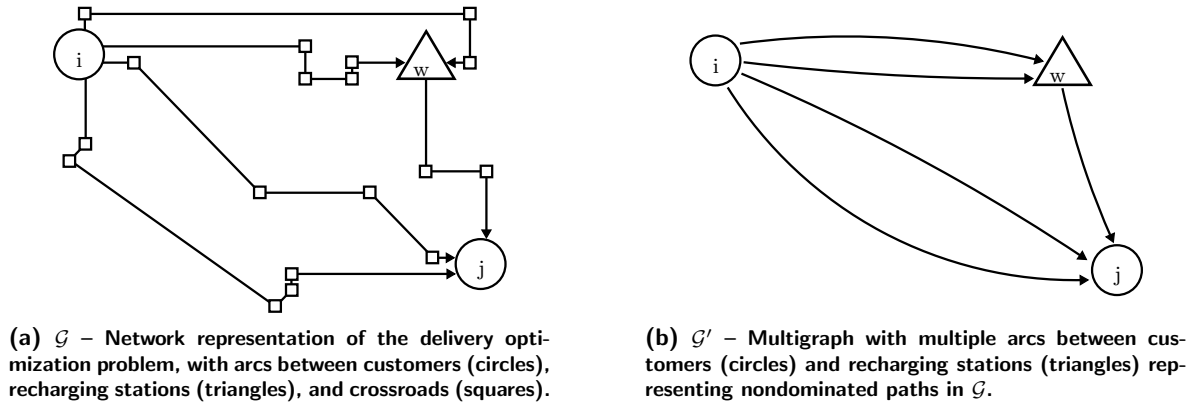


Figure 1: Graph representation and multigraph reformulation.

vehicle types may differ for fuel or electricity consumption and costs, as well as freight capacity  $Q^k$ . Accordingly, non-dominated paths (as introduced above) may differ between vehicle types.

With this notation, we refer to a solution  $\Pi$  as a set of tuples  $(\pi, k)$ , each defining a route  $\pi$ , and the vehicle type used to operate on the corresponding route. We define a route  $\pi = \{(0, i, k, l), \dots, (i', 0, k, l')\}$  as an ordered set of consecutive arcs which starts and ends at a central depot 0 and includes visits to customers in order to provide service or to recharging stations in order to recharge a vehicle's battery.

### Constraints

A solution  $\Pi$  remains feasible if it meets the following feasibility constraints:

1. Vehicles may depart from the depot 0 at any time after  $e_0$  but must return before  $l_0$ .
2. Each customer  $v_i \in \mathcal{C}$  must be visited by exactly one vehicle, ensuring that
  - (a) the accumulated demand of all customers visits of a route  $\pi$  may not exceed the corresponding vehicle type's capacity  $Q^k$ .
  - (b) delivering freight at a customer starts within  $[e_i, l_i]$ . A vehicles must wait if it arrives before  $e_i$ .
  - (c) vehicles can only depart after finishing the freight delivery which lasts  $s_i$  minutes.
3. **ECV** types  $k \in \mathcal{K}^B$  have a battery capacity of  $Y^k$  kilowatt hours. The battery's state of charge
  - (a) is  $Y^k$  when leaving the depot.
  - (b) must not fall below zero along a route
  - (c) cannot exceed the maximum capacity  $Y^k$  when recharged at a recharging station  $v_i \in \mathcal{R}$ .

We allow partial recharging. For simplicity, we approximate the recharging time as a linear function of the amount of energy charged, with a recharging rate  $g$ . Such an assumption is appropriate for en-route recharging and represents a worst case approximation, given the concave shape of a recharging function.

#### *Fees and access restrictions*

We consider the five access restriction policies as listed in Table 1:

- The first two models (F1 and F2) are either based on a fee  $\xi^E$ , that is paid for each entry into the city center (F1), or on a daily fee  $\xi^D$ , which is paid only once (F2).
- In the distance-based model (F3), a fee  $\xi^\delta$  proportional to the driven distance is paid whenever the vehicle traverses an arc within the city center.
- In the time-based model (F4), a fee  $\xi^T$  is paid per time unit spent (driving, waiting, or servicing) in the city center.
- Finally, model (F5) prohibits **ICEVs** from entering city centers.

The fees associated with models (F1) and (F3), as well as fees proportional to the driving time in model (F4) can be directly included in the variable routing costs. Daily fees (F2) are added when the vehicle enters the city center for the first time. Time-based fees of model (F4) require additional calculations of service and waiting time within the city center. Finally, model (F5) constitutes an extreme case of models (F1), (F2), (F3), and (F4) where the fees for **ICEVs** are set to arbitrarily high values ( $\xi^E = \infty$ ,  $\xi^D = \infty$ ,  $\xi^\delta = \infty$ , and  $\xi^T = \infty$ ).

### Objective function

The objective minimizes the total cost consisting of fixed and operational cost. The fixed costs  $f^k$  depend on the assignment of vehicle type  $k$  and represent the sum of acquisition (e.g., leasing or amortized price), maintenance and driver costs. Operational costs result from the sum of costs for all arcs  $c_{ijl}^k$  traversed by the fleet and incurring fees.

Let  $\Xi^\pi$  be the routes' fees not included in the variable routing costs ( $\Xi^\pi = 0$  in case of **ECVs**). Furthermore, let  $\Pi^k$  be all routes  $\pi$  of the solution  $\Pi$  with vehicle type  $k$  assigned. Then the objective  $Z(\Pi)$  is calculated as follows:

$$Z(\Pi) = \sum_{k \in \mathcal{K}} \sum_{\pi \in \Pi^k} (f^k + \sum_{(i,j,k,l) \in \pi} c_{ijl}^k + \Xi^\pi) \quad (1)$$

Since the mixed fleet and routing problem presented above is NP-hard, we develop an efficient metaheuristic algorithm to derive solutions in the next sections.

## 2.2 Route optimization algorithm

To find high-quality solutions for each model, we use a tailored **hybrid genetic algorithm (HGA)** (Vidal et al., 2012, 2014) combined with efficient labeling techniques (Hiermann et al., 2019) for route evaluations. Algorithm 1 shows general structure of a search iteration.

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**Algorithm 1** Pseudocode of a search iteration showing the HGA components used in this work.

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```

1: function HGA_ITERATION( $i, \mathcal{P}, \mathcal{S}, x^*$ )
2:   if  $i \bmod 50 = 0$  then
3:      $x \leftarrow \text{SOLVE\_SET\_PARTITIONING}(\mathcal{S})$ 
4:   else
5:      $p_1 \leftarrow \text{BINARY\_TOURNAMENT}(\mathcal{P})$ 
6:      $p_2 \leftarrow \text{BINARY\_TOURNAMENT}(\mathcal{P})$ 
7:      $o \leftarrow \text{OX\_CROSSOVER}(p_1, p_2)$ 
8:      $x \leftarrow \text{SPLIT}(o)$ 
9:    $\text{LOCALSEARCH}(x)$ 
10:  if  $\text{FEASIBLE}(x)$  &  $x < x^*$  then  $x^* \leftarrow x$ 
11:   $\text{UPDATE\_PENALTIES}(x)$ 
12:   $\text{UPDATE\_ROUTE\_SET}(x, \mathcal{S})$ 
13:   $\text{MANAGE\_POPULATION}(x, \mathcal{P})$ 

```

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This **HGA** iteratively generates new solutions by selection, crossover, and local search. These solutions are added into the population and the worst ones—in terms of cost and contribution to the population diversity—are progressively eliminated to direct the search toward promising areas of the search space. The algorithm terminates as soon as  $n^{\text{MAX}}$  successive iterations without improvement of the best solution have been performed.

**Search Space.** Since it is known that a controlled exploration of infeasible solutions can help transitioning between feasible solutions, our algorithm allows penalized intermediate solutions with violations of the route capacity and time-window constraints. The penalties are proportional to the amount of constraint violations, and their weights are dynamically adapted (Vidal et al., 2014).

**Generation of new solutions.** Each new solution is generated by recombining two *parents* selected by binary tournament (Goldberg and Deb, 1991) and applying a local search (LS) on the resulting solution. As in Prins (2004), we use the OX crossover on a giant-tour representation of the solutions,

followed by a dynamic-programming-based SPLIT algorithm to obtain individual routes. Our LS is based on classical neighborhood operators (Vidal et al., 2014): 2-OPT, inverting a subsequence of visits within a single node, 2-OPT\*, splitting two routes and reconnecting them differently, RELOCATE and SWAP, relocating or exchanging customer visits, and VEHICLE-SWAP, which changes the vehicle type and class allocated to a route. These moves are evaluated in random order and any improving move is directly applied. The LS stops when no improving move exists in the neighborhoods (local minimum). If the resulting solution includes penalized constraint violations, the penalty values are temporarily increased by a factor of 10 and another LS is applied. This step is performed one last time with the penalties multiplied by 100 if the solution remains infeasible. No further attempts are taken to remove constraint violations.

Moreover, we use a variety of speed-up techniques. First we preprocess a set of *promising* edges for each customer location, using the *customer correlation measure* described in Vidal et al. (2014), and we restrict our search to the moves that generate at least one promising edge. Second, we exploit cost lower bounds to quickly filter moves involving ECVs that have no chance of solution improvement. To that extent, we ignore battery capacity constraints and recharging stations in a preliminary evaluation of the move. If the move leads to a better objective, we perform the lengthier ECV calculations to determine its exact value. Otherwise, the move can be discarded as it cannot lead to a better solution. Finally, a cache memory keeps track of the move evaluations provided the routes involved in the move are unchanged.

**Population management.** Finally, our population management remains the same as in Hiermann et al. (2019). Infeasible and feasible solutions are managed in two separate subpopulations containing between 5 and 15 solutions. Every time the maximum population size is attained, a survivor-selection phase is triggered to eliminate the worst solutions in terms of quality and contribution to population diversity. Moreover, a set-partitioning integer programming formulation is solved every 50 iterations in an attempt to combine the previously discovered routes into a new best solution.

## 2.3 Efficient route evaluations

In the solution method, each route  $r$  is represented as an itinerary of customer visits, starting and ending at the depot, but with no information on the arcs used or recharging stations visited. During move and route evaluations, a labeling procedure makes these decisions by solving a *resource-constrained shortest path problem (RCSPP)* (Irnich and Desaulniers, 2005) on a subgraph of the multigraph  $\mathcal{G}'$  which contains only the nodes visited and the arcs connecting them to their direct successor in route  $r$ . We describe in this section the RCSPP for ICEVs to illustrate the general procedure. The process is similar for ECVs, with some additional calculations which are detailed in the Appendix.

We use a resource extension functions (REF) framework to determine the new values of the resources when appending a vertex to a sequence. The functions required for routes of ICEVs are the following:

$$T_j^Q = T_i^Q + q_j \quad (2)$$

$$T_j^{\text{COST}} = T_i^{\text{COST}} + c_{ijl}^k + \begin{cases} (s_j + \Delta^{\text{WT}}) \cdot \xi^T & i, j \in \mathcal{S} \\ s_j \cdot \xi^T & i \notin \mathcal{S}, j \in \mathcal{S} \vee i \in \mathcal{S}, j \notin \mathcal{S} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$T_j^{\text{DUR}} = T_i^{\text{DUR}} + t_{ijl}^k + s_j + \Delta^{\text{WT}} \quad (4)$$

$$T_j^{\text{E}} = \max\{T_i^{\text{E}}, e_j - \Delta\} - \Delta^{\text{WT}} \quad (5)$$

$$T_j^{\text{L}} = \min\{T_i^{\text{L}}, l_j - \Delta\} + \Delta^{\text{TW}} \quad (6)$$

$$T_j^{\text{TW}} = T_i^{\text{TW}} + \Delta^{\text{TW}} \quad (7)$$

where  $\Delta = T_i^{\text{DUR}} - T_i^{\text{TW}} + t_{ijl}^k$ ,  $\Delta^{\text{WT}} = \max\{0, e_j - \Delta - T_i^{\text{L}}\}$ , and  $\Delta^{\text{TW}} = \max\{0, T_i^{\text{E}} + \Delta - l_j\}$ .

Equation (2) extends the demand fulfilled by the vehicle, whereas Equations (4) to (7) track the minimum duration of the route, the earliest (latest) departure from the depot, and the time-window

violations. The resource representing the cost, given in Equation (3), includes the arc-based driving costs and access restriction policy fees, as well as fees proportional to the time spent servicing a customer and possibly waiting until the next start of service in the city center. Waiting in the city center should be avoided whenever possible to minimize cost. The unavoidable amount of waiting time is represented by  $\Delta^{\text{WT}}$ . When  $i, j \in \mathcal{S}$ , this waiting time occurs in the center and therefore the time-based fee is applied. Otherwise, the vehicle can depart later from  $i$  and arrive on time at  $j$ , or wait at  $j$  to reduce waiting costs.

We now describe the general labeling procedure. The resources of each ICEV label  $L$  are represented as  $R^{\text{ICEV}}(L) = \{v(L), T^{\text{COST}}(L), T^{\text{E}}(L), T^{\text{DUR}}(L)\}$ , where  $T^{\text{COST}}(L)$  represents the cost,  $T^{\text{E}}(L)$  represents the earliest departure from the depot,  $T^{\text{DUR}}(L)$  is the duration and  $v(L)$  is the last vertex visited. Let  $\{\sigma_0, \sigma_1, \sigma_2, \dots\}$  be the sequence of customer visits representing a route. Then the labeling procedure, starting with a single label at the depot  $\sigma_0$ , iteratively extends the labels from  $\sigma_i$  to  $\sigma_{i+1}$  through the arcs of  $\mathcal{G}'$ . While extending, a dominance criterion is used to eliminate labels; a label  $L_2$  is dominated by  $L_1$  whenever:

$$v(L_1) = v(L_2) \quad (8)$$

$$T^{\text{COST}}(L_1) \leq T^{\text{COST}}(L_2) \quad (9)$$

$$T^{\text{E}}(L_1) + T^{\text{DUR}}(L_1) \leq T^{\text{E}}(L_2) + T^{\text{DUR}}(L_2). \quad (10)$$

Equation (8) ensures that only labels ending in the same node are compared. This is implicitly ensured by the iterative extension of labels. To dominate another label, the cost has to be lower or equal (9). Finally (10) ensures that the earliest begin of service of  $L_1$  is lower or equal than for  $L_2$ , such that  $L_2$  could never turn out to be better due to a lower degree of time window constraints violations.

This dominance rule effectively limits the growth of the number of labels and contributes to the efficiency of the route evaluation algorithm.

### 3 Design of experiments

We aim to derive general decision support for municipalities analyzing the impact of different access restriction policies. To reduce the risk of structural bias that may result from focusing on a single city, we consider three different case studies for the cities of Paris (France), Vienna (Austria), and New York (USA). As shown in Figure 2, these cities have different sizes, spatial structures, and population densities.

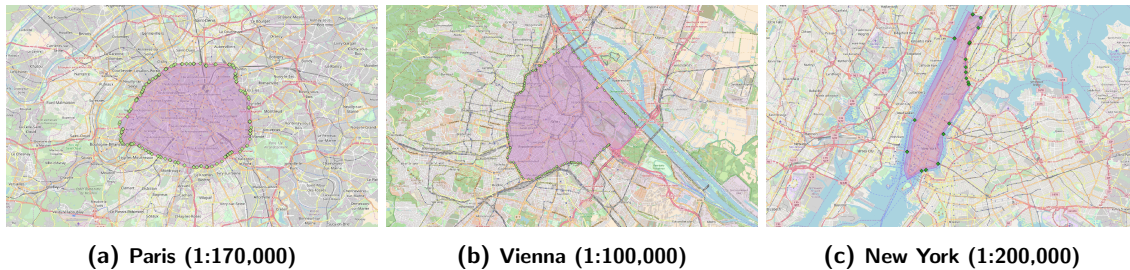


Figure 2: Cities used in the experiments (scales measured in meters).

*Paris* has a population of 2.2 million inhabitants in an area of 105 km<sup>2</sup>. With another 4.3 million people in close proximity, it is one of the most populated urban areas in Europe. The city is surrounded by a ring road, the "Boulevard Périphérique" which we choose as the border of the city center.

*Vienna* is spread over an area of 414 km<sup>2</sup> with a slightly lower population of 1.9 million inhabitants. We choose the area inside a road surrounding a central part of Vienna, the "Gürtel", as its city center.

*New York* is the most populous city in the United States, with 8.5 million inhabitants in an area of around 780 km<sup>2</sup>. We choose the island of Manhattan with its natural border formed by the surrounding river (and thus limited access points) as the city center.

We obtained spatial information and road data from [OpenStreetMap \(OSM\)](#). This data includes the locations of shops and charging stations; therefore it reflects the structural differences of the cities. When creating an instance, we randomly select 200 shops that must be served, 80 within the city center and 120 outside, and consider all available charging stations to obtain a realistic delivery scenario. To avoid a bias from different charging station capacities, we treat all the charging stations as 11 kWh type-2 chargers. We assume the depot of the [LSP](#) to be at an arbitrary point in an industrial area outside the city center: in “Zone Industrielle du Râteau” (Paris), Danube Harbor (Vienna), and Brooklyn (New York). We use artificial customer demands selected in [0.5,10], and vehicle capacities of 100 and 125, such that vehicles perform an average of 20 to 22 customer visits, a typical number of stops that we observed in field projects. We use a planning horizon of eight hours, representing a single driver shift. Accordingly, the depot and the charging-station time windows are set to [0h,8h]. We randomly select typical values for the customer time windows from [30min, 2h] and the service times from [3min, 10min]. For each city, we create 20 instances with different customer locations, time windows, and service times.

Table 2 shows the vehicle types that we consider. For both [ICEVs](#) and [ECVs](#), we consider a small vehicle (IC1, EC1) and a medium vehicle (IC2, EC2) differing in terms of cost, consumption, and freight volume. Note that we increased the consumption of the [ECVs](#) by 20% compared to their data sheet values to conservatively account for average load and additional sources of consumption (Taefi, 2016). We consider a single delivery day, where the operational cost, i.e., consumed fuel/electricity and applicable fees, depends on the routing decisions. The calculation of the fixed costs of using a vehicle is similar to the commonly used [TCO](#) calculation. We assume that vehicles are used for four years and 250 days per year before being resold. Then the fixed cost  $f^k$  for a vehicle of type  $k$  on a per day basis is calculated as

$$f^k = \frac{1}{250} \left( \frac{1}{4} \left( \beta_k^{\text{ACQ}} - \frac{\beta_k^{\text{SELL}}}{(1+\tau)^4} \right) + \sum_{i=0}^3 \frac{\beta_k^{\text{MPY}}}{(1+\tau)^i} \right) + \beta^{\text{DCPD}}, \quad (11)$$

where  $\beta^{\text{ACQ}}$  is the acquisition cost,  $\beta^{\text{SELL}}$  the gain from reselling a vehicle of type  $k$  after four years,  $\beta^{\text{MPY}}$  is the maintenance cost per year, and  $\beta^{\text{DCPD}}$  is the driver cost per day. The discount rate  $\tau$  is set to 5%. The reselling gain and maintenance cost were derived from Plötz et al. (2013), assuming a vehicle drives a total of 25,000 km per year.

**Table 2: Vehicle classes and types used in the experiments.**

	<a href="#">ICEV</a>		<a href="#">ECV</a>	
	IC1	IC2	EV1	EV2
Vendor	Volkswagen	Volkswagen	Streetscoter	Streetscoter
Name	Caddy-Maxi	Transporter	Work	Work-L
Acquisition cost	20620.0	26225.0	35950.0	45450.0
Reselling gain	10310.0	13112.5	16177.5	20452.5
Maintenance cost (€/year)	1475.0	1475.0	1225.0	1225.0
Driver cost (€/hour)	18.0	18.0	18.0	18.0
Load capacity [%]	100	125	100	125
Liter/100 km, kWh/100 km	5.8	7.9	20.2	23.4
€/liter, €/kWh	1.3	1.3	0.3	0.3
Battery (kWh)			20	40

**Experimental setup.** We conduct two different experiments. The first experiment (E1) involves a base case scenario, whereas the second experiment (E2) focuses on sensitivity analyses for different scenario parameters. In both cases, we consider a variety of city-center access fees policies and levels: daily fees  $\xi^D \in [1, 2, \dots, 15]$  €/day, entry-based fees  $\xi^E \in [1, 2, \dots, 15]$  €/entry, distance-based fees  $\xi^\delta \in [0.05, 0.10, \dots, 0.60]$  €/km, and time-based fees  $\xi^T \in [0.2, 0.04, \dots, 0.5]$  €/min.

- E1 – Impact of city center access restrictions.** We analyze the impact of city center access restrictions on the economic viability of *ECVs*. We first solve the unpenalized case, i.e., each case study *without considering restrictions*. Then we solve the most penalized case by *prohibiting ICEVs from entering the city center*. We also consider four access restrictions, two event-based fees: *a daily fee*, and *a per-entry fee*, and two volume-based fees: *a distance-based fee*, and *a time-based fee* for driving inside the city center. All fees apply only to *ICEVs*.
- E2 – Sensitivity analysis.** The second experiment analyzes the effect of varying the problem attributes as summarized in Table 3. For each variation, i.e., reduced capacity, larger time windows, and a smaller city center, we repeat Experiment 1.

**Table 3: Scenarios tested in Experiment E2.**

S0) Default	Basic settings of Experiment E1.
S1) Reduced transport capacity	All vehicle types have only half their previous transport capacity, which requires additional vehicles to serve the demand.
S2) Increased time windows	Earliest (latest) start of service is reduced (increased) by half of the time-window length. If the new value exceeds the minimum (maximum) time of the instance, the time window is shifted, such that it stays within the planning horizon, or contains it.
S3) Smaller city center	We define a smaller area where the restrictions apply: for Paris the districts (arrondissements) 1 to 4, in Vienna the first district, and in New York City Upper Manhattan (above 96th Street).

## 4 Results

This section discusses our results for the base case scenario (Section 4.1) and our subsequent sensitivity analyses (Section 4.2). To reduce the chance of bias, we collected all the solutions of an instance and cross-evaluated these over all experimental variations (restriction policies) for each experimental setting (city, size, load capacity, time-window length). Our discussion is based on the resulting best solutions.

### 4.1 Impact of city center access restrictions

Table 4 first analyzes the fleet composition and the resulting distances traveled for each vehicle type. The first column shows the policy used as well as a fee range that yields the corresponding solution. The remaining columns present the fleet composition (i.e., the number of different *ECVs* and *ICEVs* used), the distance traveled inside and outside the city center, and the total distance traveled.

For all three case studies, we observe similar effects, which shows that the different restriction policies appear to be fairly robust to different spatial layouts. In all case studies, prohibiting *ICEVs* from city centers does not increase the total number of vehicles used but causes a fleet transformation toward an *ECV* share of roughly 60%. It also increases the total distance traveled by 5% (Vienna) to 12% (Paris). Focusing on volume-based fees (daily and per-entry), one can see that for all case studies a high fee (10€–13€) is necessary to obtain the same solution as in the prohibited case. For Vienna and Paris, the daily and per-entry-based fees are equal, which shows that vehicles enter the city center only once. In general, the solutions are the same for large fee ranges in Paris and Vienna. In New York, the per-entry and daily fees differ and the former has a much more granular correlation between the fee and the resulting fleet operations. The distance-based fee has the most granular correlation for Vienna and Paris. However, the solutions show no changes in fleet composition until a high fee is set; instead, there is an inverse in the total distance traveled. This results from changes in the vehicle routes to minimize the distance traveled (and thus charged) within the city center.

Figure 3 gives an example of this effect, showing the route pattern for a subset of customers served by the same vehicle for the unrestricted case and with a fee of €0.30/km. As can be seen, the vehicle uses a longer route to avoid fees in the latter scenario. In the unrestricted scenario, the vehicle uses a



**Table 4: Fleet composition and total distance traveled for different scenarios, decomposed by vehicle type and distance (in km) inside and outside the city center.**

city	policy	IC1			IC2			EV1			EV2			total dist.
		#v	in	out	#v	in	out	#v	in	out	#v	in	out	
Paris	unrestricted	2	39.4	128.1	7	185.8	377.5	0	0.0	0.0	0	0.0	0.0	730.8
	daily [1,12]	2	0.0	242.6	7	197.1	345.9	0	0.0	0.0	0	0.0	0.0	785.6
	€/day [13]	0	0.0	0.0	3	0.0	277.6	1	17.0	86.6	5	206.1	223.7	811.1
	entry [1,12]	2	0.0	242.5	7	180.1	368.1	0	0.0	0.0	0	0.0	0.0	790.7
	€/entry [13]	0	0.0	0.0	3	0.0	277.6	1	17.0	86.6	5	206.1	223.7	811.1
	dist. [0.05]	2	31.6	138.0	7	143.0	432.3	0	0.0	0.0	0	0.0	0.0	744.8
	€/km [0.1]	2	28.5	143.6	7	141.3	434.9	0	0.0	0.0	0	0.0	0.0	748.4
	[0.15]	2	25.1	152.1	7	140.7	436.3	0	0.0	0.0	0	0.0	0.0	754.1
	[0.2]	2	24.6	153.7	7	137.6	443.4	0	0.0	0.0	0	0.0	0.0	759.3
	[0.25,0.3]	2	24.6	153.7	7	135.3	451.9	0	0.0	0.0	0	0.0	0.0	765.4
	[0.35]	2	22.9	162.9	7	135.3	451.9	0	0.0	0.0	0	0.0	0.0	773.0
	[0.4,0.45]	2	22.0	195.2	4	31.1	373.4	0	0.0	0.0	3	175.9	93.5	891.0
	[0.5]	0	0.0	0.0	3	0.0	277.6	1	17.0	86.6	5	206.1	223.7	811.1
	time [0.02,0.04]	2	39.6	177.9	7	191.6	338.1	0	0.0	0.0	0	0.0	0.0	747.2
	€/min [0.06]	1	34.0	59.7	8	211.6	460.9	0	0.0	0.0	0	0.0	0.0	766.2
	[0.08,0.44]	2	34.9	174.5	4	86.0	298.0	0	0.0	0.0	3	175.9	93.5	862.9
	[0.46,0.5]	0	0.0	0.0	3	37.5	234.6	1	17.0	86.6	5	206.1	223.7	805.6
	prohibited	0	0.0	0.0	3	0.0	277.6	1	17.0	86.6	5	206.1	223.7	811.1
Vienna	unrestricted	5	59.6	258.9	4	92.8	124.6	0	0.0	0.0	0	0.0	0.0	535.9
	daily [1,7]	5	23.1	285.4	4	114.0	120.5	0	0.0	0.0	0	0.0	0.0	543.0
	€/day [8,12]	4	0.0	279.6	5	138.4	147.3	0	0.0	0.0	0	0.0	0.0	565.4
	[13]	4	0.0	228.7	0	0.0	0.0	0	0.0	0.0	5	157.0	173.2	558.9
	entry [1,12]	4	6.4	267.1	5	120.4	142.9	0	0.0	0.0	0	0.0	0.0	536.8
	€/entry [13]	4	0.0	228.7	0	0.0	0.0	0	0.0	0.0	5	157.0	173.2	558.9
	dist. [0.05]	5	31.3	274.2	4	89.9	141.4	0	0.0	0.0	0	0.0	0.0	536.9
	€/km [0.1]	5	31.1	274.6	4	88.9	143.1	0	0.0	0.0	0	0.0	0.0	537.8
	[0.15]	5	31.1	274.6	4	86.0	149.6	0	0.0	0.0	0	0.0	0.0	541.3
	[0.2]	5	31.1	274.6	4	84.9	152.7	0	0.0	0.0	0	0.0	0.0	543.3
	[0.25]	5	30.8	275.8	4	84.1	154.5	0	0.0	0.0	0	0.0	0.0	545.1
	[0.3]	5	30.8	275.8	4	83.5	156.6	0	0.0	0.0	0	0.0	0.0	546.6
	[0.35]	4	20.9	243.3	5	82.3	190.0	0	0.0	0.0	0	0.0	0.0	536.5
	[0.40]	4	0.9	261.5	1	0.0	66.4	1	37.5	26.5	3	110.2	88.0	591.1
	time [0.02,0.06]	5	84.2	228.7	4	71.4	156.5	0	0.0	0.0	0	0.0	0.0	540.8
	€/min [0.08,0.14]	5	72.7	263.4	2	22.0	95.5	0	0.0	0.0	2	106.2	57.1	616.8
	[0.16,0.50]	4	12.6	247.3	1	0.7	65.4	1	37.5	26.5	3	110.2	88.0	588.3
	prohibited	4	0.0	228.7	0	0.0	0.0	0	0.0	0.0	5	157.0	173.2	558.9
New York	unrestricted	2	43.3	297.7	7	110.5	270.3	0	0.0	0.0	0	0.0	0.0	721.7
	daily [1,9]	2	48.4	251.0	7	88.2	327.0	0	0.0	0.0	0	0.0	0.0	714.5
	€/day [10,11]	1	0.0	68.8	6	96.0	240.0	1	31.5	135.6	1	35.4	141.9	749.3
	[12]	1	0.0	92.0	3	0.0	183.2	1	18.4	86.8	4	174.0	236.3	790.6
	entry [1]	2	48.2	251.1	7	88.2	327.0	0	0.0	0.0	0	0.0	0.0	714.5
	€/entry [2,3]	2	48.4	250.9	7	88.2	327.0	0	0.0	0.0	0	0.0	0.0	714.4
	[4]	2	48.2	252.9	7	88.2	327.0	0	0.0	0.0	0	0.0	0.0	716.3
	[5,8]	1	17.4	99.6	7	125.2	322.9	1	15.8	157.9	0	0.0	0.0	738.8
	[9]	2	0.0	138.7	3	27.2	135.5	0	0.0	0.0	4	174.4	312.3	788.2
	[10]	1	0.0	92.0	3	0.0	183.2	1	18.4	86.8	4	174.0	236.3	790.6
	dist. [0.05,0.1]	2	39.9	259.4	7	88.2	327.0	0	0.0	0.0	0	0.0	0.0	714.5
	€/km [0.15,0.4]	2	38.4	263.1	7	88.2	327.0	0	0.0	0.0	0	0.0	0.0	716.6
	[0.45]	1	0.0	92.0	3	0.0	183.2	1	18.4	86.8	4	174.0	236.3	790.6
	time [0.02,0.08]	2	36.3	269.0	7	124.8	302.3	0	0.0	0.0	0	0.0	0.0	732.5
	€/min [0.10,0.14]	2	19.8	258.9	4	30.3	230.7	0	0.0	0.0	3	144.8	135.9	820.4
	[0.16]	2	19.2	273.1	3	0.0	187.3	0	0.0	0.0	4	178.8	185.9	844.3
	[0.18]	1	0.0	92.0	3	0.0	183.2	1	18.4	86.8	4	174.0	236.3	790.6
	prohibited	1	0.0	92.0	3	0.0	183.2	1	18.4	86.8	4	174.0	236.3	790.6

much shorter city center route that is no longer economically viable with a fee of €0.30/km. For New York, we observe a less granular correlation for distance-based fees. This is because the city can only be reached via long bridges or tunnels, which reduces the number of shortcuts and thus the possible detours to avoid fees.

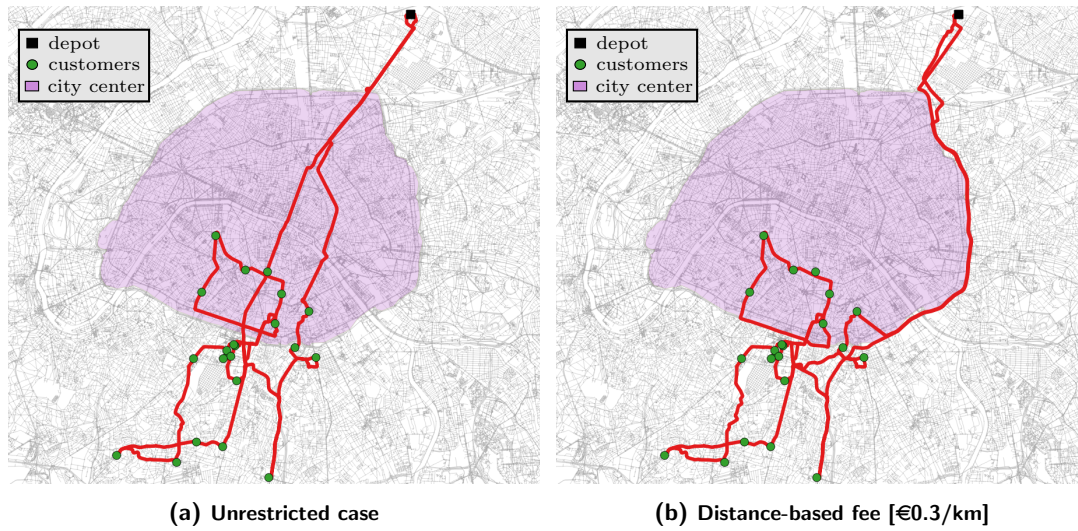


Figure 3: Example of fee-induced detours with distance-based fee.

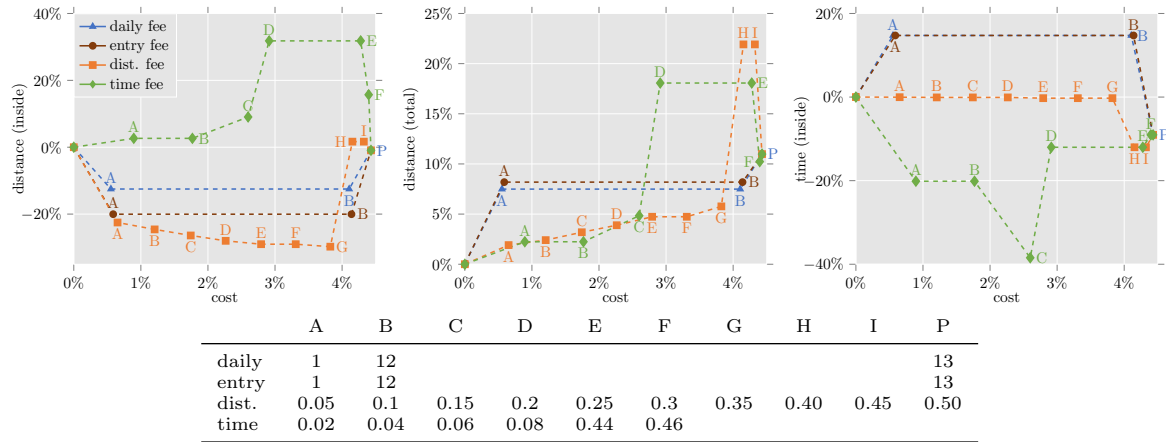
Time-based fees also have a less granular correlation. However, compared to all other strategies, imposing a small time-based fee (e.g., €0.10/min in New York) shifts the fleet composition toward an [ECV](#) share of 33.33%. This policy penalizes both the distance driven and the time spent on customer service inside the city center. Since this time cannot be adjusted, [ECVs](#) are the only viable option for reducing the fees. Overall, it is possible to match the solution of the prohibited case with each policy if a sufficiently high fee is chosen.

Figure 4 shows how the different policies influence the [LSP](#)'s cost and how this affects either the distance traveled within the city center (left), the total distance traveled (middle), or the time spent in the city center (right) compared to the unrestricted scenario. Each data point corresponds to the solution with minimal cost found for a given policy fee, listed in the table below the graphs. Fee values resulting in solutions equivalent to the prohibited case are shown in column 'P'. As already outlined, with sufficiently high fees, all policies converge to the prohibited scenario solution with a mild increase in total distance traveled and a mild decrease in time spent within the city center. However, the impact of the policies differs significantly for fee values that do not enforce the prohibited-scenario solution. We can identify three general trends. First, all policies except the time-based fee reduce the distance traveled within the city center. The time-based fee instead increases the distance traveled within the city center because the overall time spent within the center rather than the distance traveled is reduced. Second, a per-entry fee increases the time spent in the city center to reduce the number of entries. Note that for both of these effects, the [LSP](#) shifts customer orders between different vehicles. Third, if the distance-based fees are not high enough, the distance traveled within the city center decreases but the total distance driven increases by up to 40%. Accordingly, a distance-based policy with the wrong fee values may increase total traffic by shifting it to outer areas, as shown in Figure 3.

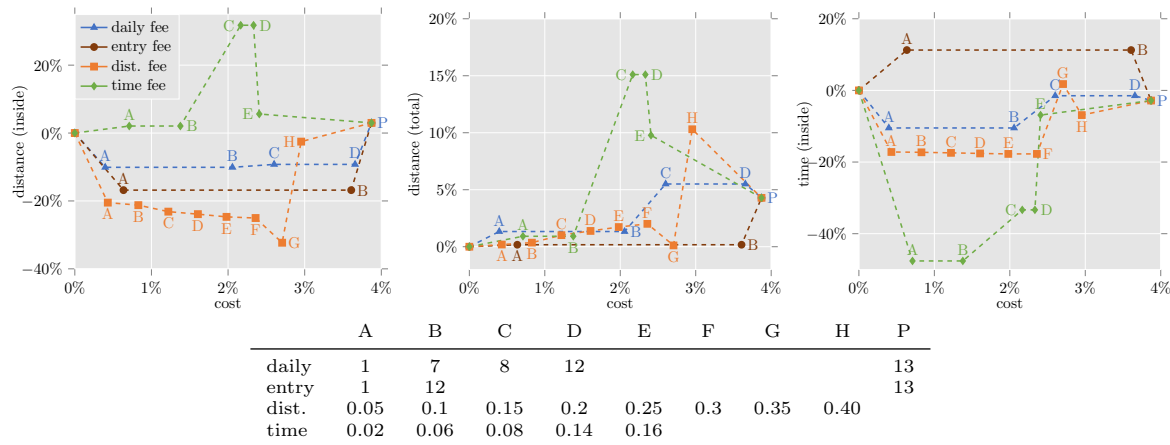
To analyze the impact of restriction policies on CO<sub>2</sub> emissions, we calculated these emissions a posteriori for all scenarios, assuming 152.4 gCO<sub>2</sub>/km (type-1) and 187.2 gCO<sub>2</sub>/km (type-2) for [ICEVs](#), and 103.0 gCO<sub>2</sub>/km (type-1) and 119.0 gCO<sub>2</sub>/km (type-2) for [ECVs](#), based on 474gCO<sub>2</sub>/kWh emitted during production of the electricity in the power grid (Icha, 2019). Figure 5 shows these emissions for each case study, policy, and fee range on a relative scale compared to the unrestricted scenario. As can be seen, a maximum reduction of up to 10%–16% can be achieved in the prohibited case. However, as noted above for distance increases, an inverse effect may result for certain fees and policies, and the total CO<sub>2</sub> emissions may increase by up to 10% when restriction policies are applied in the wrong fashion.



## (a) Paris



## (b) Vienna



## (c) New York

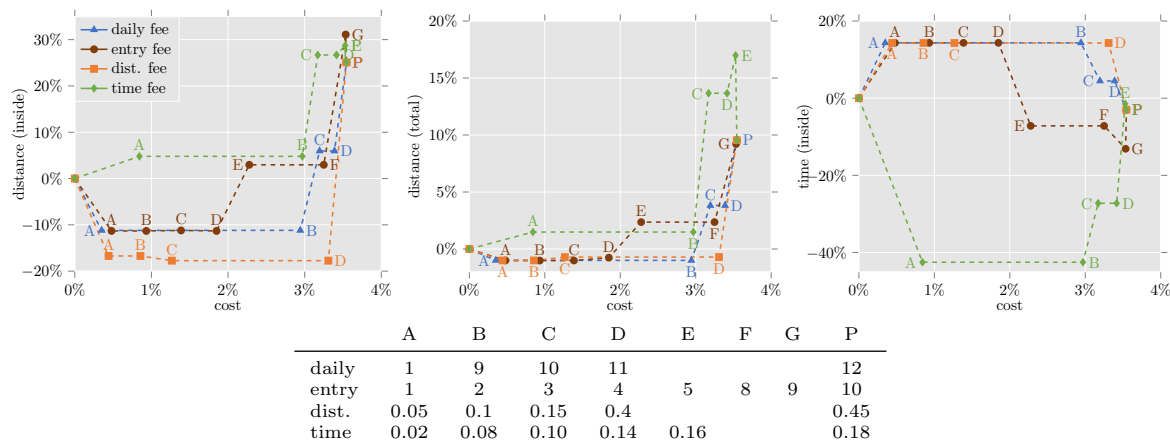


Figure 4: Increase in distance (in total or within the city center) or time, and cost compared to the unrestricted solution. Tables show the fee values for all points labeled in the graphs.

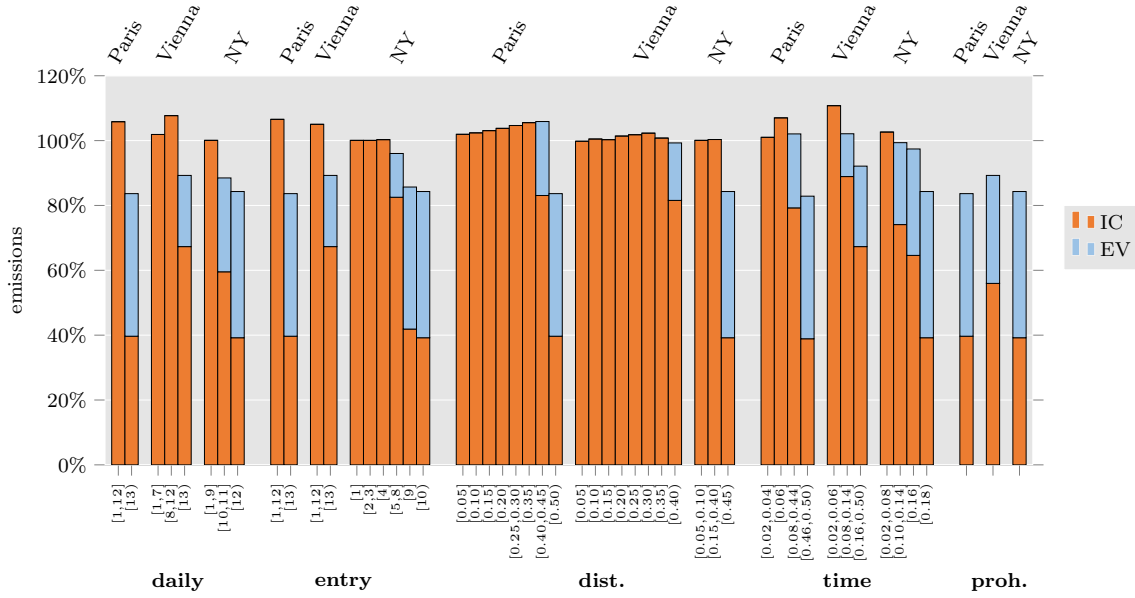


Figure 5: Total CO<sub>2</sub> emissions (%) with 100% being the result of the unrestricted case.

## 4.2 Sensitivity analyses

We now perform a sensitivity analysis to generalize the findings of Section 4.1. We are interested in the maximum improvement potential that can be reached in a different setting. Since Section 4.1 showed that, for sufficiently high fees, all policies converge to the solution of the prohibited case, we limit our discussion to a comparison of the unrestricted and prohibited cases.

Table 5 details the increase in cost, distance traveled, time spent within the city center, fleet size, and *ECV* fleet share between the unrestricted and the prohibited scenario for our base case (S0), a reduced vehicle capacity (S1), larger customer time windows (S2), and a smaller city center (S3). As can be seen, a reduction of the city center size worsens the *ECV* ratio by 50%, whereas a reduced vehicle capacity worsens the *ECV* ratio by only 10% for all three case studies. Larger time windows may improve or worsen the *ECV* share depending on the case study. These adverse effects result from the increased flexibility in the route design, which can favor *ICEV* usage in the unrestricted case or *ECV* usage in the prohibited case. Since the *ECV* share reflects the potential impact of the restriction policy, the other quantities are correlated. An exception occurs for New York, where the time spent inside the city center remains the same for a smaller city center size. This can be explained by the city center's location on the island of Manhattan, where the limited number of entry and exit points reduces the options for alternative schedules. Independent of the scenario, the fleet size remains constant.

While Table 5 analyzes the impact of city center access restrictions for each scenario, Table 6 compares changes between the additional scenarios (S1–S3) and the base case (S0) for the unrestricted and prohibited cases. As can be seen, the costs are nearly doubled for S1 in which the vehicle capacity decreases; this increase results from a proportional increase in the fleet size. However, the *ECV* share remains equal for Paris and New York, whereas it decreases by 15% for Vienna. For the other scenarios, the fleet size remains nearly constant. Accordingly, changes in total cost vary only slightly by less than 10% because the changes in the fleet composition and operation are sufficient to balance the operational costs. With larger time windows (S2), the share of *ECVs* decreases by up to 20% for each case study, whereas a reduced city center size (S3) reduces the share of *ECVs* in the prohibited case by up to 80%.

**Table 5: Change in cost, distance traveled inside or in total, time inside the city center, fleet size, and ECV ratio for the prohibited case relative to the unrestricted case.**

		cost (%)	dist. inside (%)	dist. total (%)	time inside (%)	#v (%)	ECV ratio (%)
Paris	base case (S0)	+4.43	-0.93	+10.98	-9.04	0.0	+66.7
	reduced vehicle capacity (S1)	+3.93	-11.48	+16.26	-8.01	0.0	+55.6
	large time windows (S2)	+3.92	+7.40	+18.58	-22.95	0.0	+55.6
	smaller city center (S3)	+1.16	-11.62	+1.75	-43.46	0.0	+11.1
Vienna	base case (S0)	+2.79	+14.55	+2.92	+8.56	0.0	+55.6
	reduced vehicle capacity (S1)	+0.20	-16.79	-0.88	+0.76	0.0	+47.1
	large time windows (S2)	+0.32	-17.53	-0.82	+3.01	0.0	+62.5
	smaller city center (S3)	+0.98	+33.40	+0.08	-41.95	0.0	+11.1
New York	base case (S0)	+3.54	+25.07	+9.55	-2.99	0.0	+55.6
	reduced vehicle capacity (S1)	+3.62	+19.73	+5.01	-6.82	0.0	+55.6
	large time windows (S2)	+3.23	+7.21	+18.55	+6.71	0.0	+44.4
	smaller city center (S3)	+0.68	+46.26	+5.78	0.00	0.0	+11.1

**Table 6: Change in cost, distance traveled inside or in total, time inside the city center, fleet size, and ECV ratio for each scenario relative to the base case.**

		cost (%)	dist. inside (%)	dist. total (%)	time inside (%)	#v (%)	ECV ratio (%)
Paris	unrestricted S0→S1	+96.44	+35.15	+17.06	+63.08	+100.0	0.0
	S0→S2	-0.88	-17.92	-16.96	+13.48	0.0	0.0
	S0→S3	-0.07	-86.67	+0.19	-67.78	0.0	0.0
	prohibited S0→S1	+95.50	+20.75	+23.63	+64.93	+100.0	0.0
	S0→S2	-1.36	-11.01	-11.27	-3.87	0.0	-16.67
	S0→S3	-3.20	-88.11	-8.15	-79.97	0.0	-83.33
Vienna	unrestricted S0→S1	+92.23	+45.29	+36.65	+83.57	+88.9	0.0
	S0→S2	-7.27	+16.01	-3.19	-6.86	-11.1	0.0
	S0→S3	-1.01	-92.06	-1.83	-79.41	0.0	0.0
	prohibited S0→S1	+87.39	+5.53	+31.62	+70.39	+88.9	-15.3
	S0→S2	-9.49	-16.48	-6.71	-11.62	-11.1	-12.5
	S0→S3	-2.75	-90.75	-4.54	-88.99	0.0	-80.0
New York	unrestricted S0→S1	+96.07	-1.47	+5.90	+77.71	+100.0	0.0
	S0→S2	-0.90	-15.86	-23.52	-10.80	0.0	0.0
	S0→S3	+0.07	-85.29	-1.72	-92.64	0.0	0.0
	prohibited S0→S1	+96.21	-5.68	+1.52	+70.70	+100.0	0.0
	S0→S2	-1.20	-27.88	-17.23	-1.88	0.0	-20.0
	S0→S3	-2.70	-82.80	-5.10	-92.41	0.0	-80.0

## 5 Conclusion

We have studied the impact of city center access restriction policies on logistics fleets in order to provide decision support for municipalities. To this end, we developed an algorithmic framework that mimics an LSP's decisions about fleet composition and daily operations. We applied this framework to study three different case studies for the cities of Vienna, Paris, and New York, considering a multitude of policies, namely daily fees, per-entry fees, distance-based fees, and time-based fees for ICEVs that enter the city center. We compared the results from these scenarios to an unrestricted case and to a full prohibition of ICEVs in city centers. We analyzed how different policies affect an LSP's strategic and operational behavior and if such policies can encourage the adoption of ECVs in city logistics. Additionally, we analyzed the impact on emissions. To generalize our findings, we conducted additional sensitivity analyses for all case studies, focusing on a vehicle's freight capacity, the width of the delivery time windows, and the size of the city center. Our results lead to the following managerial insights.

**Fee-based restrictions can enforce the same solution as a complete ban of ICEVs from city centers.** Our results show that independent of the fee policy, one can match the prohibited-scenario

solution if fees are chosen appropriately. However, these fees turn out to be very high for volume-based policies, whereas fees in line with current practice result for event-based policies.

**Event-based fee policies are more robust than volume-based policies.** Volume-based fee policies may have adverse effects, i.e., worsen the solution compared to the unrestricted case, if the fees are chosen incorrectly. The values that cause adverse effects vary because volume-based fees also tend to be more sensitive to spatial and structural differences. In contrast, event-based (daily or per-entry) fees do not cause adverse effects.

**Besides reducing local emissions in city centers, access restrictions can help to reduce greenhouse gas emissions.** Although restriction policies increase the total distance, total CO<sub>2</sub> emissions can be reduced by up to 16% if the right policies are applied with the right fees. However, volume-based fees in particular may lead to increased CO<sub>2</sub> emissions if the wrong fees encourage LSPs to compensate fees with detours.

**The size of the city center greatly impacts the effectiveness of restriction policies.** Our results show that if the size of the (restricted) city center is too small, restriction policies have only a minor impact on logistics fleet operations.

## A Appendix: Route evaluations for ECVs

Section 2.3 described the route evaluation procedures for ICEVs. In a similar fashion, this appendix defines the REFs for ECV routes, and explains how resource values change when a sequence is extended to an additional vertex. Due to the number of variables involved, we describe the intermediate calculations (starting with  $\Delta$ ) only briefly where they occur and give the details at the end of the section. First we list the resources involved at a certain state  $i$ :

- $T_i^{\text{COST}}$  – total cost for electricity consumed
- $T_i^{\text{Q}}$  – load capacity used (customer demands fulfilled)
- $T_i^{\text{DUR}}$  – total route duration
- $T_i^{\text{TW}}$  – accumulated time warp (local time window violations which are repaired by ‘traveling back in time’; see Vidal et al., 2014)
- $T_i^{\text{Y}}$  – available electricity in the battery
- $T_i^{\text{EY}}$  – sum of all energy constraint violations (electricity requirements exceeding the state of charge at that time).
- $T_i^{\text{YAR}}$  – amount of electricity that can be recharged at the last visited station
- $T_i^{\text{TAR}}$  – time available to recharge at the last visited station

The REFs for ECVs are then defined as follows:

$$T_j^{\text{COST}} = T_i^{\text{COST}} + c_{ijl}^k \quad (12)$$

$$T_j^{\text{Q}} = T_i^{\text{Q}} + q_j \quad (13)$$

$$T_j^{\text{DUR}} = T_i^{\text{DUR}} + t_{ijl}^k + s_j + \Delta^{\text{WT}} + \Delta^{\text{RC}} \quad (14)$$

$$T_j^{\text{TW}} = T_i^{\text{TW}} + \Delta^{\text{TW}} + \Delta^{\text{TWRC}} \quad (15)$$

$$T_j^{\text{Y}} = T_i^{\text{Y}} - r_{ij} + \Delta^{\text{Y}} + \Delta^{\text{YWT}} \quad (16)$$

$$T_j^{\text{EY}} = T_i^{\text{EY}} + \Delta^{\text{EY}} \quad (17)$$

$$T_j^{\text{YAR}} = \begin{cases} Y - (T_i^{\text{Y}} - r_{ijl}^k + \Delta^{\text{Y}} + \Delta^{\text{YWT}}) & \text{if } j \in \mathcal{R}, \\ T_i^{\text{YAR}} - (\Delta^{\text{YRC}} - \Delta^{\text{EY}} + \Delta^{\text{YWT}}) & \text{otherwise} \end{cases} \quad (18)$$

$$T_j^{\text{TAR}} = \begin{cases} \max\{0, l_j - (e_0 + \Delta^{\text{DUR}})\} & \text{if } j \in \mathcal{R}, \\ \max\{0, \min\{T_i^{\text{TAR}} - \Delta^{\text{RC}} - \Delta^{\text{YWT}} \cdot g, l_j - (e_0 + \Delta^{\text{DUR}} + \Delta^{\text{WT}})\}\} & \text{otherwise.} \end{cases} \quad (19)$$

Equations (12) and (13) define the cost  $T_i^{\text{COST}}$  and capacity  $T_i^{\text{Q}}$  resources respectively. An extension simply sums the cost of the consumed electric energy (no fees apply to ECVs) and additional load respectively. In Equation (14), the duration  $T_i^{\text{DUR}}$  is calculated by adding the travel time  $t_{ijl}^k$ , the service time  $s_j$ , the waiting time  $\Delta^{\text{WT}}$ , and the recharging time  $\Delta^{\text{TRC}}$ . The time warp  $T_i^{\text{TW}}$  is extended in (15) by adding any necessary time warp as a result of either late arrival at the customer ( $\Delta^{\text{TW}}$ ) or a battery recharging operation ( $\Delta^{\text{TWRC}}$ ). Equation (16) calculates the available electric energy of the vehicle at vertex  $j$  by subtracting the electric energy required to reach  $j$  (denoted as  $r_{ijl}^k$ ) and adding the energy recharged to reach node  $j$  ( $\Delta^{\text{Y}}$ ) as well as the amount recharged to avoid waiting time at the customer ( $\Delta^{\text{YWT}}$ ). Any violations to the energy constraints  $T_i^{\text{EY}}$  are taken into account in Equation (17).

To keep track of the available time and amount to recharge, two additional resources are needed. In Equation (18), the amount of electric energy that can be recharged at the last recharging station visited is maintained to ensure that the maximum battery capacity is respected. If  $j$  is a recharging station, the rechargeable amount  $T_j^{\text{YAR}}$  is the difference between the maximum capacity  $Y$  and the current capacity of the battery (Equation 16). Otherwise, if  $j$  is a customer or the depot, the extended resource incorporates the amount of energy actually recharged in order to reach  $j$  (i.e.,  $\Delta^{\text{YRC}} - \Delta^{\text{EY}}$ ) or used because of waiting time ( $\Delta^{\text{YWT}}$ ).

Equation (19) calculates the available time to recharge  $T_i^{\text{TAR}}$  to correctly identify the required time warp due to recharging operations. When a recharging station  $j \in \mathcal{R}$  is visited, the available recharging time is reset to the time remaining until the end of the time window. Otherwise, the minimum of two values defines the extension: 1) the previous available time minus the time required to recharge in order to reach vertex  $j$  (i.e.,  $\Delta^{\text{TRC}}$ ) and due to waiting time ( $\Delta^{\text{YWT}} \cdot g$ , where  $g$  is the inverse recharging rate), and 2) the remaining time window of the current customer.

Finally, the intermediate calculations are shown below:

$$\Delta^{\text{Y}} = \max\{r_{ijl}^k - T_i^{\text{Y}}, 0\} \quad (20)$$

$$\Delta^{\text{EY}} = \max\{\Delta^{\text{Y}} - T_i^{\text{YAR}}, 0\} \quad (21)$$

$$\Delta^{\text{TRC}} = \Delta^{\text{Y}} \cdot g \quad (22)$$

$$\Delta^{\text{TWRC}} = \max\{\Delta^{\text{TRC}} - T_i^{\text{TAR}}, 0\} \quad (23)$$

$$\Delta^{\text{DUR}} = T_i^{\text{DUR}} - T_i^{\text{TW}} + \Delta^{\text{TRC}} - \Delta^{\text{TWRC}} + t_{ijl}^k \quad (24)$$

$$\Delta^{\text{WT}} = \max\{e_j - \Delta - e_0, 0\} \quad (25)$$

$$\Delta^{\text{TW}} = \max\{e_0 + \Delta - l_j, 0\} \quad (26)$$

$$\Delta^{\text{YWT}} = \min\{T_i^{\text{YAR}} - \Delta^{\text{Y}}, \min\{T_i^{\text{TAR}} - \Delta^{\text{TRC}}, \Delta^{\text{WT}}\}/g\}, \quad (27)$$

where Equation (20) calculates the additional electricity required to reach vertex  $j$ . Any amount of electricity that cannot be recharged at a previously visited recharging station is calculated in Equation (21). In Equation (22), the time required to recharge the missing amount is determined, whereas Equation (23) holds the time warp required to satisfy the time-window constraint. The actual duration up to vertex  $j$  is calculated using Equation (24), which determines the corresponding waiting time (Equation 25) and time warp (Equation 26). Finally, Equation (27) determines the recharging time that can replace waiting at vertex  $j$ .

We now describe the general labeling procedure. Each label is characterized by the following resources:

$$R^{\text{ECV}}(L) = \{v(L), T^{\text{COST}}(L), T^{\text{DUR}}(L), T^{\text{Y}}(L), T^{\text{YAR}}(L), T^{\text{TAR}}(L)\}, \quad (28)$$

where  $T^{\text{COST}}(L)$  is the cost of label  $L$ ,  $T^{\text{DUR}}(L)$  the time duration at  $v(L)$ , and  $T^{\text{Y}}(L)$  the current energy level.  $T^{\text{YAR}}(L)$  is the rechargeable energy and  $T^{\text{TAR}}(L)$  the maximum recharging time at the last recharging station visited. These values are directly obtained from the extension functions described earlier in this section.

Let  $\{\sigma_0, \sigma_1, \sigma_2, \dots\}$  be the customer visits of a given route. To evaluate this route, the labeling procedure starts with a single label at the first node ( $\sigma_0$ ) and iteratively extends the labels associated with  $\sigma_i$  to  $\sigma_{i+1}$  using the arcs of  $\mathcal{G}''$ . By dominance, a label  $L_2$  can be eliminated if there exists another label  $L_1$  such that:

$$v(L_1) = v(L_2) \quad (29)$$

$$T^{\text{COST}}(L_1) \leq T^{\text{COST}}(L_2) \quad (30)$$

$$T^{\text{DUR}}(L_1) \leq T^{\text{DUR}}(L_2) \quad (31)$$

$$T^Y(L_1) + \min\{T^{\text{YAR}}(L_1), T^{\text{TAR}}(L_1)/g\} \geq T^Y(L_2) + \min\{T^{\text{YAR}}(L_2), T^{\text{TAR}}(L_2)/g\} \quad (32)$$

$$(T^Y(L_1) \geq T^Y(L_2)) \vee (T^{\text{DUR}}(L_1) + (T^Y(L_2) - T^Y(L_1)) \cdot g \leq T^{\text{DUR}}(L_2)) \quad (33)$$

This criterion states that label  $L_1$  has a lower cost (30), a shorter duration (31), and a higher maximal available energy (32), i.e., the current level plus the rechargeable amount. Moreover, the available electric energy must be higher or the total duration must be shorter after recharging the missing amount, as described in Equation (33).

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