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RESEARCH PAPER

Alternative e-commerce delivery policies

A case study concerning the effects on carbon emissions

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Abstract Contemporary shopping habits are undergoing rapid change, with more and more consumers purchasing goods online. The rapid growth of the online retail sector provides great opportunities for both wholesalers and transporters in servicing this newly emergent type of customer. With both consumers and corporations acutely aware of the environmental impact of business activities, one of the most relevant research questions is how to organize the operations of a e-commerce delivery business while simultaneously minimizing its environmental impact. The present paper addresses the *e-commerce delivery problem*, a mathematical formulation and fast heuristics which enable the simulation of various e-commerce delivery scenarios. The effects of the scenarios regarding more environmentally friendly e-commerce concerns are tested upon real-world data. In particular, the impact of new green(er) technology (such as electric bicycles and cars), aggregated collection points, carrier bundling, and changing delivery times is investigated. The obtained results are suitable for implementation at an organizational or operational level within both e-commerce delivery companies and transporters.

Keywords E-commerce delivery problem · Mixed-fleet vehicle routing · Operational policies

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1 Introduction

There is an ongoing shift from the traditional, physical shopping environment towards online shopping. With annual online purchasing growth estimated at roughly 10% within Europe, it is not difficult to imagine a near future, where online shopping overtakes in-store sales and becomes the new normal. Wholesalers promise the fast delivery of products to customers; however, the logistical process itself is organized by road couriers and transporters. While offering a high level of comfort to individual customers, e-commerce delivery practices represent a considerable source of greenhouse emissions. In addition, urban areas are particularly vulnerable to complicating factors such as traffic congestion due to their high density of both residential and commercial destinations. The rapid growth of online shopping, or e-commerce, correlates with important environmental and societal challenges imposed by governments and environmentally conscious consumers, namely: how one may operationally organize e-commerce deliveries, such that their environmental impact is minimal, and how to simultaneously satisfy customer demands while minimizing transportation costs. Indeed, online wholesalers and transporters are eager to discover viable answers to these questions.

Many businesses have adopted a consumer direct (CD) model, which permits customers to purchase goods online and have them delivered directly to their addresses. Duin et al (2007) provide an auctioning model which assigns orders to providers in a cost and punctuality-driven environment. Orders arrive dynamically, requiring flexibility concerning their insertion into routes. Campbell and Savelsbergh (2006) detailed various incentive policies, encouraging companies to pursue home deliveries. They presented the home delivery problem with time slot incentives, where customers select a delivery time slot based upon the associated monetary benefits being offered by the company. However, the environmental impact of such policies was not studied.

Bektaş and Laporte (2011) introduced an extension of the vehicle routing problem with time windows (VRPTW), the pollution routing problem (PRP), the objective of which is to minimize a cost function composed of emission costs, fuel costs, and driver costs. The study concluded that the cost of working hours dominates the emission cost. Demir et al (2012) also studied the PRP and proposed an ALNS algorithm with a specialized speed optimization component capable of computing optimal speeds on a given path. Çağrl et al. (2014) extended the PRP by considering a heterogeneous fleet which only contained internal combustion commercial vehicles (ICCVs). They conducted experiments on instances from the literature and discovered that using a heterogeneous fleet without speed optimization reduces operational costs by a greater degree than when employing a homogeneous fleet with speed optimization.

Employing a homogeneous fleet of electrical vehicles was considered by Schneider et al (2014) during their E-VRPTW study (the addition of 'E' signifying 'Electrical'). The objective of the E-VRPTW is to minimize the distances traveled by electric commercial vehicles (ECVs). Schneider et al (2014) presented a mixed integer programming (MIP) model and metaheuristics to solve their generated instances. Goeke and Schneider (2015) studied E-VRPTWMF, an extension of E-VRPTW, where two vehicle types were considered as a mixed-fleet (MF): ECVs and conventional ICCVs. This study proposed a more realistic energy consumption model for ECVs based on individual vehicle mass, speed, and the terrain's gradient. Three different minimization objectives were considered: distance traveled; the sum of vehicle propulsion and labor cost; and battery replacement cost. All experiments were conducted upon randomly generated instances. Desaulniers et al (2016) study the E-VRPTW with time windows, given an unlimited fleet of identical ECVs. They particularly focus on the electric vehicles' limited autonomy and investigate variants, where vehicles may recharge once, several times, partially or fully during the course of a route.

In recent years, green logistics has received increasing interest due to growing environmental concerns by citizens and governments. Roberti and Wen (2016) address the electric traveling salesman problem with time windows (ET-SPTW) which considers the limited capacity of existing electric vehicle batteries, thereby acknowledging the need for intermediate stops at recharging stations. Heuristics were developed and tested on generated instances. El-Berishy and Scholz-Reiter (2016) considered a homogeneous fleet with a single depot VRP. They proposed a two stage stochastic model, where the delivery speed and emissions are uncertain. The first stage generates optimum routes; the second stage minimizes emissions by regulated vehicles' speed. Koç and Karaoglan (2016) addressed the green-VRP by considering a homogeneous fleet, limited driving range and refueling infrastructure. They developed a branch and cut algorithm and tested it upon a benchmark set with 20 customers. Leggieri and Haouari (2017) solved the green-VRP by integer programming and outperform Koç and Karaoglan (2016)'s algorithm. Shao et al (2016) focus on avoiding congestion while investigating distribution strategies. Ehmke et al (2016) modeled expected emissions costs as a function of the time at which the vehicle begins traveling an arc and its load while traversing some arc. They did not factor in waiting times. Huang et al (2017) considered path selection in time-dependent vehicle routing problems (TDVRP-PF), where any arc between two customer nodes represents multiple paths. A homogeneous fleet of vehicles was considered to minimize fuel consumption and vehicle depreciation cost. Huang et al (2017) modeled the TDVRP-PF both under deterministic and stochastic traffic conditions and generated instances based on Beijing's road network. Muñoz-Villamizar et al (2017) investigated, similar to the present paper, both the delivery cost and environmental impact of employing a homogeneous ECV fleet in an urban environment. They modeled a multi-depot vehicle routing problem (MDVRP) and experimented with real-world data obtained from a transportation network in Bogotá, Colombia.

Several successful approaches within the VRP literature proposed various types of population-based evolutionary algorithms to address different variants of the problem. Nagata et al (2010) and Koç et al (2015) presented a hybrid genetic algorithm for the VRP with time windows. Tasan and Gen (2012) employed a genetic algorithm for the VRP with simultaneous pick-up and deliveries. Meanwhile, Vidal et al (2012) developed an evolutionary algorithm which combines population-based evolutionary search and neighborhood-based metaheuristics to address three VRPs: multi-depot, periodic, and the multi-depot periodic with capacitated vehicles. Vidal et al (2013) presented a hybrid genetic search with diversity control for a large class of time-constrained vehicle routing problems. All referenced studies conducted extensive computational experiments on academic benchmark instances. The experimental results showed that the proposed algorithms achieved high-quality solutions which encourage the usage of population-based evolutionary algorithms to address variants of the VRP.

Furthermore, there exist several survey papers within the field which highlight various aspects of green logistics and the incorporation of environmental issues into combinatorial optimization problems. Such papers most commonly focus on the vehicle routing problem (Dekker et al 2012; Demir et al 2014; Lin et al 2014).

Despite the valuable contributions made by the aforementioned studies, finding the most profitable mode of operation while simultaneously limiting greenhouse emissions on realistic problem instances remains unexplored. This subject may be addressed using three fundamental research questions: (i) how may one organize delivery from distribution center to the customer in an ecological manner? (ii) Which operational shifts may reduce emission levels without incurring unacceptable costs? (iii) Which concessions related to delivery time windows or deviation from the delivery location are acceptable for environmentally conscious consumers?

The present paper investigates the e-commerce delivery problem (EDP) from an operational perspective. The EDP generalizes the vehicle routing problem, wherein orders must be delivered to customers. Its objective is to compose routes beginning and ending at the depot and visiting each delivery location while simultaneously minimizing operational costs and emissions. In addition to traditional vehicle routing objectives and constraints, the EDP requires the selection of vehicle types (electrical or otherwise), the determination of delivery dates, and/or the merging of delivery points.

An integer programming formulation which incorporates vehicle-dependent transportation costs and greenhouse emissions, driving times and delivery times is introduced in Sect. 2. By incorporating such factors, the impact of alternative delivery strategies—such as the introduction of a heterogeneous fleet including electric vehicles, relaxing delivery time windows, or aggregating delivery destinations—may be accurately investigated. New delivery strategies are subsequently presented during Sect. 3 and applied to real-world data provided by e-commerce delivery transporters. The availability of real-world data provides a unique opportunity to explore the effects of the proposed policies. A set of fast heuristics enabling the simulation of various e-commerce delivery scenarios is presented in Sect. 4. The performance of the proposed algorithms is analyzed followed by extensive simulations which enable the assessment of both the environmental and financial impact of such strategies. Experimental results (Sect. 5) reveal the interesting and often counter-intuitive effects of adjusting operations. The lack of research in mixed-fleet EDP means that these results will likely have an immediate impact upon online businesses and will potentially contribute to more sustainable e-commerce delivery practices.

2 Problem statement

The EDP consists of three major components: depots, vehicles, and parcels. A depot is a location from which parcels must be delivered to their associated destinations. Each depot has a set of vehicle types P, where each individual vehicle type p is associated with the following parameters: (i) number of available vehicles, m_p; (ii) maximum traveling duration, T_p; and (iii) energy capacity, R_p, detailing the fuel, battery, or energy capacity of the vehicle type.

A parcel has three properties: a delivery window, origin depot, and destination location. The delivery window consists of the earliest and latest possible delivery dates. The overall problem may be decomposed into a separate sub-problem for each depot. Parcels with the same origin depot and destination location may be bundled into one *multi-drop parcel provided their time windows are identical*. Each sub-problem is thus represented by an ordered list of multi-drop parcels, a depot and a mixed vehicle fleet of fixed size which delivers the parcels.

The EDP is often defined as an open vehicle routing problem (Li et al 2007). By contrast, this paper assumes that the transporter owns the vehicles employed for delivery—be they bicycles, cars, vans, or trucks. Drivers are required to return their vehicle to the depot after concluding their deliveries, a requirement contributing to the driver's total working time.

The EDP is formulated as a mixed integer program ($\mathcal{F}_{\text{EDP}}$) inspired by the research of Goeke and Schneider (2015) for E-VRPTWMF, where two vehicles types were considered with the possibility of recharging at certain stations. While $\mathcal{F}_{\text{EDP}}$ incorporates multiple vehicle types, it ignores both vehicle recharging and time windows. The EDP considers a single autonomous trip per vehicle. In addition, assuming high-level decision-making, the time windows are as long as the scheduling horizon. Consequently, time windows do not impact upon a manager's decision. Time windows for e-commerce deliveries are generally 1 week long, while in the EDP, the decision horizon is 1 day. Therefore, the $\mathcal{F}_{\text{EDP}}$ formulation does not explicitly take time windows into consideration, but rather aggregates all deliveries to the same destination into a single multi-drop parcel. Whereas regular single-drop deliveries take t_d time, multi-drop deliveries take t_b time for each additional parcel. Furthermore, vehicle capacity is considered sufficiently large to ignore capacity constraints.

The EDP is defined on a complete directed graph, $G = (V, A)$, where vertices 0 and $N + 1$ correspond to the depot, while $V_{0,N+1} = \{v_1, \dots, v_N\}$ represents the set of delivery points. The model proposed by Goeke and Schneider (2015) considers two vehicle types: ECVs and ICCVs. Given EDPs require the possibility of choosing between various vehicle types (electric vehicles, bikes, vans, and trucks), a decision variable x_{ij}^p indicates whether or not arc ij is traveled by a vehicle of type p. Given the generally light weight parcels in e-commerce, the cost of traveling an arc is assumed independent of the vehicle's load.

The proposed model aggregates all parcels requiring delivery to the same address during pre-processing into a single delivery. The demand of vertex i, q_i, represents the

Table 1 Notation

$0, N+1$	Depot vertices
V	Set of all vertices
A	Set of arcs $= \{(i,j) \mid i,j \in V, i \neq j\}$
V_0	Set of vertices excluding 0, $V_0 = \{v_1, \dots, v_{N+1}\}$
V_{N+1}	Set of vertices excluding N+1, $V_{N+1} = \{v_0, \dots, v_N\}$
$V_{0,N+1}$	Set of delivery vertices, $V_{0,N+1} = \{v_1, \dots, v_N\}$
P	Set of vehicle types
M	A big number
d_{ij}	Distance between vertices i and j
t_d	Single-drop time
t_b	Multi-drop time
t_{ij}^p	Travel time between vertices i and j by vehicle type $p \in P$
m_p	Number of available vehicles of type $p \in P$
R_p	Fuel, battery or energy capacity of vehicle type $p \in P$
T_p	Maximum tour duration of vehicle type $p \in P$
g_{ij}^p	Fuel, battery or energy consumption of vehicle type $p \in P$ between vertices i and j
h^p	Fuel, battery or energy consumption per time unit while vehicle type $p \in P$ is idle
q_i	Demand of vertex i
s_i	Service time at vertex i ($s_0, s_{N+1} = 0$)
r_i^p	Auxiliary variable indicating energy level of vehicle type p at vertex i
τ_i	Auxiliary variable for arrival time at vertex i
x_{ij}^p	Binary decision variable indicating if arc $(i,j) \in A$ is traveled by vehicle type p

number of parcels requiring delivery to vertex i. Service time at vertex $i \in V_{0,N+1}$, s_i, may be obtained by Eq. (1), where t_d and t_b represent single- and multi-drop times, respectively:

$$s_i = t_d + (q_i - 1)\, t_b. \tag{1}$$

Table 1 summarizes the notation employed throughout the paper.

$$\sum_{j \in V_0} \sum_{p \in P} x_{ij}^p = 1 \quad \forall\, i \in V_{0,N+1} \tag{2}$$

$$\sum_{j \in V_{N+1}} x_{ij}^p - \sum_{j \in V_0} x_{ji}^p = 0 \quad \forall\, i \in V, \quad p \in P \tag{3}$$

$$\sum_{j \in V_{0,N+1}} x_{0j}^p \leq m_p \quad \forall\, p \in P \tag{4}$$

$$\tau_i + \sum_{p \in P} (s_i + t_{ij}^p)\, x_{ij}^p - M\,(1 - \sum_{p \in P} x_{ij}^p) \leq \tau_j \quad \forall\, i \in V_{N+1}, \quad j \in V_0 \tag{5}$$

$$\tau_i + s_i + t^p_{i,N+1}\, x^p_{i,N+1} \leq T_p \quad \forall\, p \in P, \quad i \in V_0 \tag{6}$$

$$r^p_i - h^p.s_i.x^p_{ij} - g^p_{ij}.x^p_{ij} + R_p\,(1 - x^p_{ij}) \geq r^p_j \quad \forall\, i \in V, \quad j \in V_{N+1}, \quad p \in P \tag{7}$$

$$0 \leq r^p_i \leq R_p \quad \forall\, i \in V_{0,N+1}, \quad p \in P \tag{8}$$

$$\tau_i \geq 0 \quad \forall\, i \in V \tag{9}$$

$$x^p_{ij} \in \{0,1\} \quad \forall\, (i,j) \in A, \quad p \in P \tag{10}$$

Constraints (2) ensure that each customer is followed by exactly one other customer in the route, except for the depot vertices. Constraints (3) are flow conservation constraints guaranteeing an equal number of incoming and outgoing arcs for each vertex. Constraints (4) express an upper limit for the number of employed vehicles of each type. Auxiliary variable τ_i represents the vehicle's arrival time at vertex i and Constraints (5) link the arrival times at vertices i and j. Constraints (6) prevent each tour's total time from exceeding the maximum traveling duration of its vehicle type. Each tour's total time is obtained by summing the arrival time to the last vertex (l), τ_l, the service time of l, s_l and the travel time from l to the depot, t^p_{lN+1}. Auxiliary variable r^p_i represents the energy level of vehicle type p at vertex i. Constraints (7) set the energy level of vehicle type p at vertex j considering the energy level at its previous vertex i. Constraints (8) restrict the fuel, battery, or energy level of vehicle type p to be between zero and the maximum vehicle capacity at each vertex i. Constraints (9) state variables x^p_{ij} as binary.

The following key performance indicators (KPIs) are considered during this study:

- CO_2 emissions associated with a parcel's delivery.
- Delivery cost.
- Total distance traveled by all vehicles.
- Number of vehicles required to satisfy all deliveries.

Operators wish to minimize the linear combination of these KPIs which results in the formation of the objective function, denoted as F in Eq. (11). The term f_e within this equation denotes the total emission cost for parcel delivery, f_l the routing cost of delivery, f_d the total distance traveled by all vehicles, and f_v the total number of vehicles required to satisfy all deliveries. f_l, f_d, and f_v denote internal KPIs, whereas f_e is called an external KPI. α, β, γ, and δ are positive coefficients weighting the objectives:

$$F = \alpha f_e + \beta f_l + \gamma f_d + \delta f_v, \tag{11}$$

CO_2 emissions are derived by summing both a vehicle's travel and stationary (when ran idle) fuel consumption and then multiplying this total by the amount of CO_2 per fuel unit, c_e^p (the fuel unit may correspond to liter for diesel/gasoline, kilogram for CNG and kWh for electricity). By always considering the average consumption of vehicles when they are either traveling or stationary, their actual load at every stage of the route may be ignored. g_{ij}^p indicates the fuel consumption of vehicle type p

between vertices i and j, whereas h^p denotes vehicle-type p's fuel consumption per time unit, while it is idle at service points:

$$f_e = \sum_{i \in V_0} \sum_{j \in V_{N+1}} \sum_{p \in P} c_e^p \,.\, (g_{ij}^p + h^p s_i) \,.\, x_{ij}^p. \tag{12}$$

The delivery cost consists of labor costs and vehicle costs which include vehicle write off, fuel consumption, insurance, and maintenance. Parameters c_d and c_v^p denote driver wages per time unit and vehicle costs per kilometer for vehicle type p, respectively:

$$f_l = \sum_{i \in V_{N+1}} \sum_{p \in P} c_d \, (\tau_i + s_i + t_{i,N+1}^p) \, x_{i,N+1}^p + \sum_{i \in V_{N+1}} \sum_{j \in V_0} \sum_{p \in P} c_v^p \,.\, d_{ij} \,.\, x_{ij}^p. \tag{13}$$

The total distance is the sum of the length of all routes. The distance between vertices i and j is denoted by d_{ij}:

$$f_d = \sum_{i \in V_{N+1}} \sum_{j \in V_0} \sum_{p \in P} d_{ij} \,.\, x_{ij}^p. \tag{14}$$

The number of vehicles required:

$$f_v = \sum_{p \in P} \sum_{j \in V_{0,N+1}} x_{0j}^p. \tag{15}$$

A VRP instance may be considered an instance of the EDP with only one vehicle type and hence be solved by any EDP algorithm. Thus, the EDP is at least as hard as the VRP which is proven $\mathcal{NP}$-hard (Lenstra and Kan 1981). Therefore, exact approaches to the EDP, based on a commercial integer programming solver, are unlikely to be applicable in real-life e-commerce delivery routing due to their size, both from a financial and performance perspective.

3 E-commerce delivery policies

3.1 Alternative parcel delivery vehicles

The vast majority of current e-commerce parcels are delivered by diesel vans (Dekker et al 2012). While these vans have a low internal cost—they are cheap to buy, run, and maintain—their external cost is much greater in urban environments. Given the inefficiency of diesel engines for short trips and slow start–stop traffic, CO_2 and NO_x emissions are considerable during city tours. Furthermore, van engines are often left idle (rather than being shut off) during delivery, exacerbating emission levels.

Despite alternative delivery technologies being widely available, the potential decrease in external cost is often outweighed by the perceived increase in internal cost. Higher purchase prices and minimal difference in CO_2 emissions often discourage companies to make the transition from low-cost diesel vans to compressed natural gas (CNG) vehicles. Similarly, the high purchase price and smaller capacity of electric vans are considered economic deal breakers for companies considering the use of environmentally friendly vehicles. In (sub)urban environments, however, smaller vehicles are rarely an issue when the depot is located close to (or within) the city and only minor changes must be made to the delivery company's operations.

The impact of switching from diesel to CNG or electric vehicles is analyzed in greater detail during Sect. 5.2.1.

3.2 Collection points

Customers making purchases via e-commerce channels may have their goods delivered directly to their home, to a chosen collection point, or they may even choose to retrieve goods themselves at the company's physical store. When a customer's order exceeds a certain value, delivery fees are often waived. While it is cheaper for both e-commerce stores and carriers to deliver goods to a collection point or have them picked-up directly from the store, most online stores select home delivery by default—rarely offering any financial motivation for customers to alter their delivery method. Including more options or steps to the checkout process of online shopping significantly decreases the conversion rate (item views to sales), which is the primary reason for not offering alternative delivery options. An important downside associated with home delivery is that most people are away from home during daytime hours, which is precisely when carriers also work. This results in high delivery failure rates, whereby couriers must attempt to deliver parcels two or more times before the customer is at home to accept delivery. Not only is this very expensive for the carrier, it is also very inconvenient for the customer, since goods are delivered far later than anticipated.

It is highly plausible that, given some small financial incentive, many customers would choose to have their goods delivered to a collection point rather than at home. Customers are consequently able to collect their purchases at the time most convenient for them while simultaneously being financially rewarded for this decision. From the web shop and carrier's perspectives, this decision is also beneficial, since they are able to ship and deliver parcels at a lower cost and no longer run the risk and cost of having multiple failed deliveries.

The impact of relocating a portion of all parcels to collection points on both internal and external costs is discussed in Sect. 5.2.2.

3.3 Carrier bundling and regional monopolies

In practice, different carriers often deliver parcels to the same street on the same day. Instinctively, one would perhaps consider this situation inefficient and conclude that it would be better to offer a monopoly to a single carrier on such streets in urban centers.

Rural regions, on the other hand, often have so few parcels to be delivered that it becomes very expensive for carriers to deploy or maintain activities in such areas. In this situation, regional monopolies could likely increase the density of parcels for a single carrier and thereby engender a profit margin as opposed to several different carriers generating losses in the region. This higher parcel density also translates into decreased emissions per parcel, thus decreasing the external cost.

The effects of enforcing regional monopolies are investigated within several scenarios in Sect. 5.2.3.

3.4 Delivery times

The vast majority of e-commerce parcels are delivered directly to the customer's door. While the time spent traveling from the van to the customer's door is rather small, the time spent waiting at the customer's door after ringing the door bell easily increases average parcel delivery times to 3–4 min. This waiting time represents a significant proportion of the total delivery cost. Furthermore, many e-commerce products are packaged in boxes much larger than the product itself with the result being that carriers are mostly storing and delivering empty space to customers throughout the country. There are two logical ways of reducing long waiting times for carriers:

i. Transitioning from home delivery to collection points (see Section 3.2), or
ii. Reducing the amount of empty space in e-commerce parcels, thus enabling more parcels to be delivered via mailboxes.

The impact of reducing the time required for delivering parcels is investigated in Sect. 5.2.4.

4 Algorithms for policy simulation

Efficient algorithms are required when solving EDPs in practice. Therefore, designing easy-to-implement fast heuristics within a simulation environment is essential.

Two constructive algorithms which generate the initial solutions for the EDP are presented alongside a ruin and recreate (R&R) local search which is to be employed in combination with these constructive algorithms. Given the academic

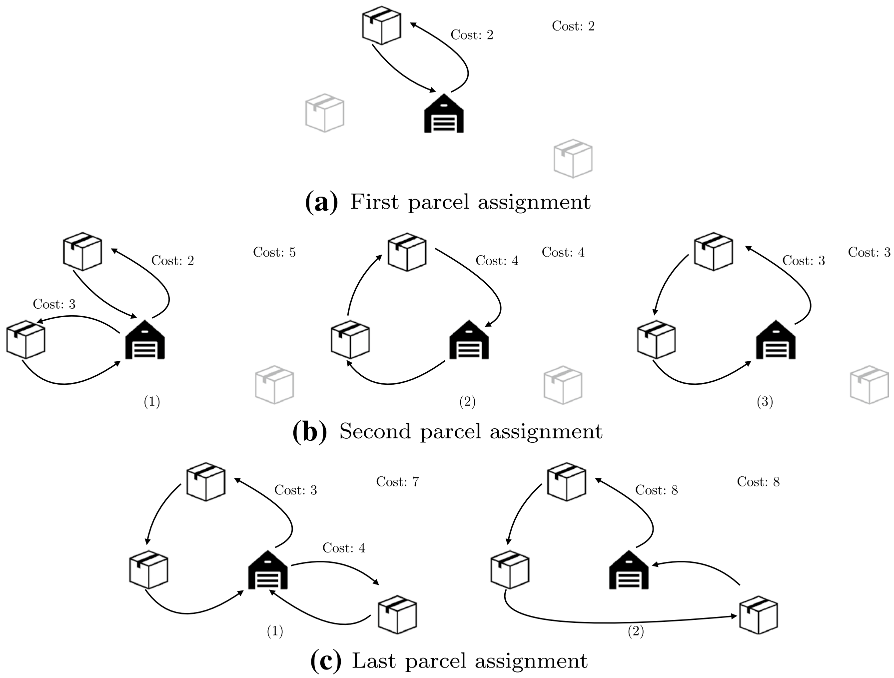


Fig. 1 CI constructive heuristic example for three parcels and one depot

merit of genetic algorithms for VRP problems, one is proposed based on the biased random-key genetic algorithm (BRKGA). Descriptions of the solution encoding and decoding heuristics, evolutionary process, and fitness function are provided.

4.1 Constructive heuristics

A cheapest insertion (CI) heuristic is applied to generate an initial EDP solution.

The heuristic creates a feasible solution for each depot by iterating over its parcel list and assigning each parcel to a delivery route. The cost of inserting each parcel at all possible positions in existing routes and of creating a new route is computed. The latter cost is obtained by inserting an available vehicle with the lowest possible emissions. Subsequently, each parcel is inserted at the lowest cost position in the route.

Once all parcels have been included in this schedule, the CI heuristic is complete and a feasible solution for the EDP is available.

Figure 1 visualizes the cheapest insertion procedure. The first parcel in the depot's list is assigned to a new route in Fig. 1a. Figure 1b illustrates how the second parcel is assigned. The cost of creating a new route for the second parcel alone (Cost 3) is compared against the cost increase when inserting it at all possible positions

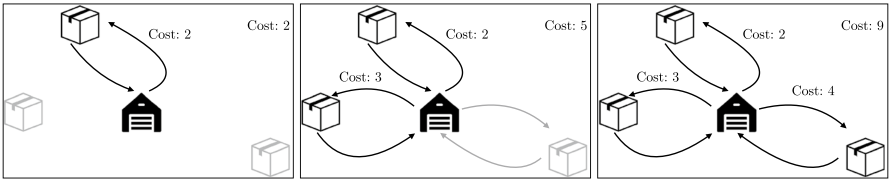


Fig. 2 One route per parcel constructive heuristic example

in the existing route. Thus, the lowest cost option (b3) is selected. The last parcel's assignment is depicted in Fig. 1c, where, similarly, the cost increase of creating a new route (Cost 4) is compared against the best possible insertion in the existing route. Note that only two possibilities are represented in the figure. The solution constructed in this example thus employs two vehicles and its cost amounts to 7.

The primary advantage of this heuristic is its capability of quickly generating solutions for even the largest instances. One noteworthy disadvantage is, however, that the algorithm produces solutions located in local optima which may prove very difficult to escape from. The combination of the standard diesel vans and electric vehicles proved challenging for the heuristic, since electric vehicles are slightly cheaper to operate and have much lower emissions than diesel vans, whereas their range is very limited. This results in solutions, where the first few parcels are loaded into the available electric vehicles, while all those remaining are loaded into diesel vans. Such solutions are far from efficient, and therefore, an alternative algorithm is proposed.

The second constructive algorithm is the one route per parcel heuristic (1RPP). This heuristic creates a solution by simply assigning each parcel to an individual delivery route. Figure 2 depicts 1RPP and clearly, although theoretically possible, its solutions incur extremely high costs. The advantage of this constructive heuristic, however, is that its resulting solution is not biased in any way and thus enables local search algorithms to efficiently alter the solution and find good quality solutions without prematurely converging to local optima.

4.2 Ruin and recreate local search

A ruin and recreate local search heuristic (Schrimpf et al 2000; Pisinger and Røopke 2007) is employed in combination with the aforementioned constructive heuristics. The R&R heuristic iteratively increases solution quality by randomly selecting a route and removing it from the solution. The removed route's parcels are re-added to the solution via CI, possibly after ordering these parcels in some way (such as decreasing distance from the depot) (Christiaens and Vanden Berghe 2016). When a new solution is associated with a lower cost than the current best solution, it replaces the latter; otherwise, a different route is selected to be ruined.

After a specified number of iterations without any cost reduction, the number of routes to ruin is increased. The R&R heuristic ends after a predefined number of non-improving iterations, either when the number of ruined routes reaches the total number of routes in the solution or when a global iteration limit is reached.

4.3 Genetic algorithm

An evolutionary algorithm, based upon the BRKGA, is proposed to identify the number of routes, types of vehicles, and parcel delivery order. BRKGA represents a variant of random-key genetic algorithms in which the initial population is composed of random-key vectors, with each vector's key being a real number sampled uniformly from the interval [0, 1). More information concerning the evolutionary process of BRKGA is provided by Gonçalves and Resende (2011).

A solution consists of a number of routes, each of which is associated with a vehicle type and parcel delivery order. This approach employs an indirect solution representation, since direct solutions would be complex to represent and manipulate during the evolutionary process. A chromosome encodes a solution as a vector of random keys. Each chromosome is composed of $n + 1$ genes, where n equals the number of parcels requiring delivery:

$$\text{Chromosome} = \left(\underbrace{gene_0}_{\text{\#routes}}, \underbrace{\text{gene}_1, \dots, \text{gene}_n}_{\text{Parcels}} \right).$$

The first gene (gene_0) identifies the number of routes per depot, while the remaining genes are *parcel* genes, each corresponding to a single parcel. Parcel genes are employed to assign their associated parcel to a route. Chromosomes are employed by the decoder when building a CFO solution. The number of routes required per depot is denoted as r and decoded via:

$$r = \left\lfloor \frac{1}{gene_0} \right\rfloor. \tag{16}$$

The decoding, or mapping, of each chromosome's last n genes into r routes is achieved by first dividing the [0, 1) interval into r sections where each section constitutes a route. Parcel p_i is assigned to route r_j if the value of gene_i lies within section j. The route index for parcels $i = 1, \dots, n$ is generated using the following expression:

$$\text{parcel's route index } i = \lfloor \text{gene}_i \times r \rfloor. \tag{17}$$

Once the parcels are assigned to the routes, the sequence of parcel deliveries per route is obtained by the greedy nearest neighbor (NN) algorithm which selects the nearest undelivered parcel as the next delivery parcel. This quickly results in a sub-optimal route, followed by a local search employing the 2-opt move (Croes 1958). Each chromosome's quality is measured by the fitness function described in Eq. (11), which feeds back into the evolutionary process.

5 Experiments and discussion

The experimental section is subdivided into three parts. The first compares the proposed algorithms, the second analyzes several existing and alternative real-world data policies, and the third highlights the insights gained via experimentation.

All experiments were performed on instances based on real-world data from e-commerce delivery carriers which details their activities for between 2 and 6 months and their regional size which ranges from a single (sub)urban environment to an area of over 30,000 km^2. The data contain over one million parcels, specifies each parcel's earliest and latest delivery date, the parcel's origin depot and finally its delivery address. Furthermore, real-world vehicle characteristics (cost per kilometer, fuel consumption, range, and driver wages) for different vehicle types were also provided by the e-commerce delivery carriers, thereby enabling a highly accurate simulation of the EDP's KPIs. Due to confidentiality and privacy issues, publishing the data in its original form is prohibited. A selection of real-world data was anonymized and posted online[1], enabling a transparent comparison of the proposed algorithms and also encouraging other researchers to compete with the proposed solution methods. All the destinations of parcels and collection points are randomized within a radius of approximately 7 m and depot locations are randomized within a radius of approximately 1 km. Vehicle characteristics were also randomized via a confidential conversion factor. Three sets of instances were thus generated: rural, suburban, and urban.

Real-world data were applied for the alternative policies, since it was deemed important to provide results on unaltered data from e-commerce delivery carriers. Consequently, only the disclosure of aggregated information is possible for these experiments. However, this information certainly suffices for the purpose of the experiments. In addition to the aggregated results, instance size and primary vehicle characteristics are also supplied for each simulation, thereby providing further insight regarding each scenario.

5.1 Algorithm analysis

The CI and R&R algorithms were implemented in Java, while the genetic algorithm was implemented via the BRKGA library in C++ 11. All experiments were executed on an Intel®Xeon®CPU E5-2640 v3 @ 2.6 GHz processor.

CI, BRKGA, CI + R&R and 1RPP + R&R were tested on three sets of instances: rural (R), urban (U), and suburban (S) instances. Experiments based on 1RPP without any improvement phase would certainly be uncompetitive and are, therefore, not considered. The 16 small instances ranging from 3 to 76 parcels correspond to the rural instances. The urban instances, meanwhile, correspond to five medium-sized instances ranging from 594 to 886 parcels. Finally, suburban instances are represented by five large instances ranging from 3743 to 5529 parcels.

[1] https://benchmark.gent.cs.kuleuven.be/hdp/.

Three fleet types are employed for rural instances: diesel (D), CNG (C), and mixed (M). Electric vehicles (E) are not employed given that some delivery points lie beyond their range. Unlike rural areas, delivery points in suburban and urban areas are close to the depot, thus enabling the utilization of electric vehicles in such regions.

Equation (11) is employed as evaluation function in all experiments. For simplicity purposes, α, β, γ, and δ are set to 1.

Given all algorithms' stochastic behavior, all reported computational results presented in this paper are based on five runs per instance. Figure 3 compares the algorithms' results obtained for rural instances employing diesel, CNG, and mixed vehicles, respectively.

The horizontal axes represent the instances and the employed fleet (R0D, for example, represents rural instance number 0 addressed with diesel vehicles). Emissions, represented on the vertical axis, are the most relevant KPI for this particular study, while also being demonstrative of the trend among all other KPIs and, therefore, constitutes an accurate indicator of solution quality.

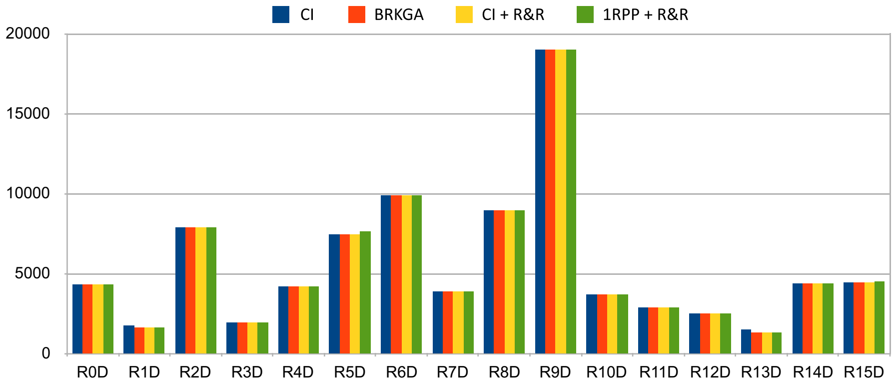
Table 2 compares the proposed algorithms in terms of number of best and worst solutions attained. The four algorithms yield solutions of identical quality for 24 out of the 48 instances. No significant performance difference between the four algorithms is noticeable with respect to the rural instances. BRKGA does, however, provide the most frequent occurrence of best solutions and least frequent occurrence of worst solutions with respect to this emissions KPI.

Figure 4 illustrates the algorithmic performance on urban instances. As the number of parcels is higher for urban than for rural instances, the BRKGA algorithm no longer clearly outperforms the other algorithms and instead competes with 1RPP + R&R for the first place.

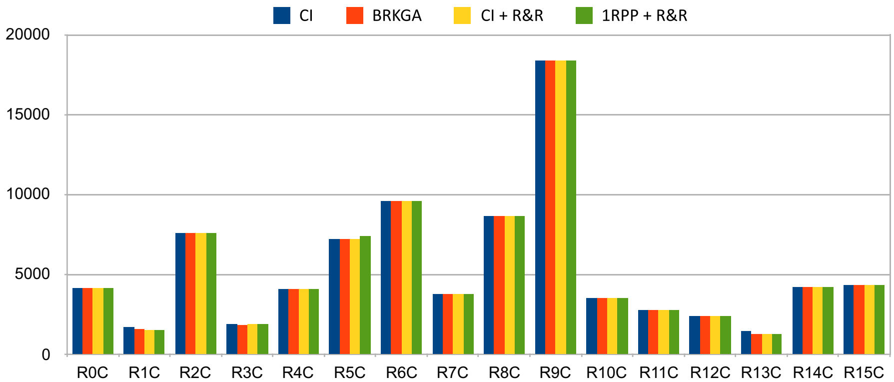
Figures 5 and 6 detail suburban instance results in terms of emissions and computational time, respectively. Figure 5 shows useful insofar as illustrating how the straightforward CI, as expected, exhibits the highest emission levels for almost all instances. BRKGA achieves better results, particularly for rural (academic-sized) instances. Finally, R&R achieves the lowest emission levels for all instances. Figure 6, meanwhile, presents computation time on a logarithmic scale, clearly illustrating how CI is (by far) the fastest-performing algorithm, with R&R taking longer and BRKGA coming in third.

In essence, while BRKGA performs best for academic-sized instances, it requires considerable computational time to reach high-quality solutions for real-world instances. Due to this scaling issue, CI represents the only viable option when tackling larger real-world instances containing up to one million parcels. Indeed, while CI's emission levels are the highest among these three algorithms, its results are most comparable to those implied by historical data sourced from the companies.

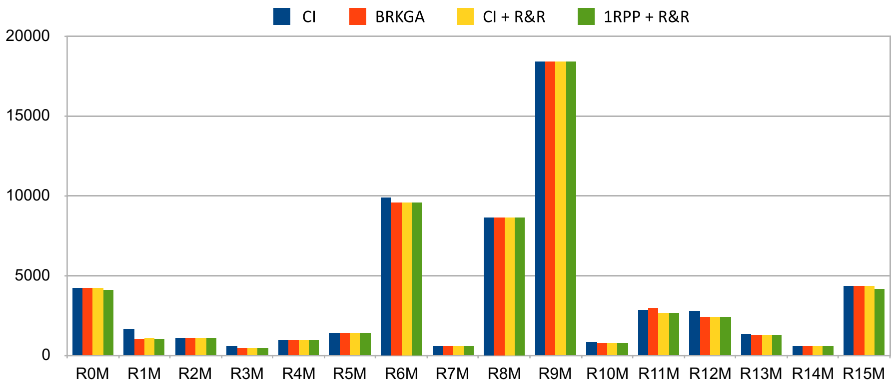
Tables 5, 6, and 7 detail the results of the four algorithms—CI, BRKGA, CI + R&R, and 1RPP + R&R—with respect to vehicle type (VT), number of parcels (#P), distance per parcel (Dis), emissions per parcel (Em), cost (€), number of routes (#R), and execution time (seconds).



(a) Algorithmic performance on rural instances with diesel vehicles.



(b) Algorithmic performance on rural instances with CNG vehicles.



(c) Algorithmic performance on rural instances with mixed vehicles.

Fig. 3 Algorithmic performance with respect to the emissions KPI on the rural (R) instances, assuming **a** diesel (D), **b** CNG (C), and **c** mixed (M) vehicles

Table 2 Comparison of algorithm performance with respect to emissions—rural instances

	CI	BRKGA	CI + R&R	1RPP + R&R
Number of best solutions	4	11	9	10
Number of worst solutions	14	3	3	9

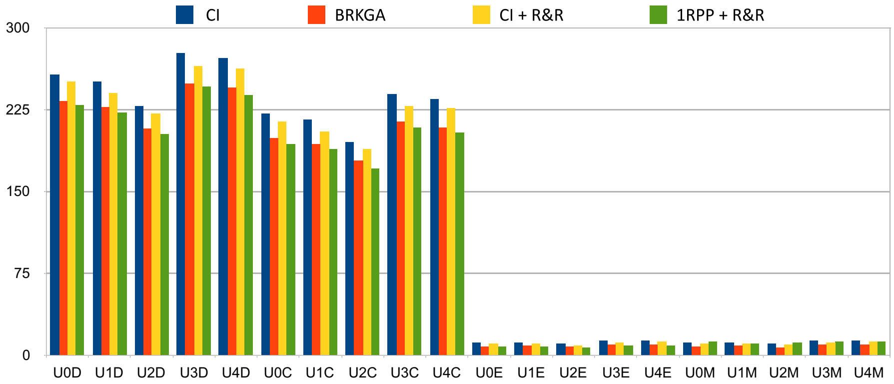


Fig. 4 Algorithmic performance with respect to the emissions KPI on the urban instances

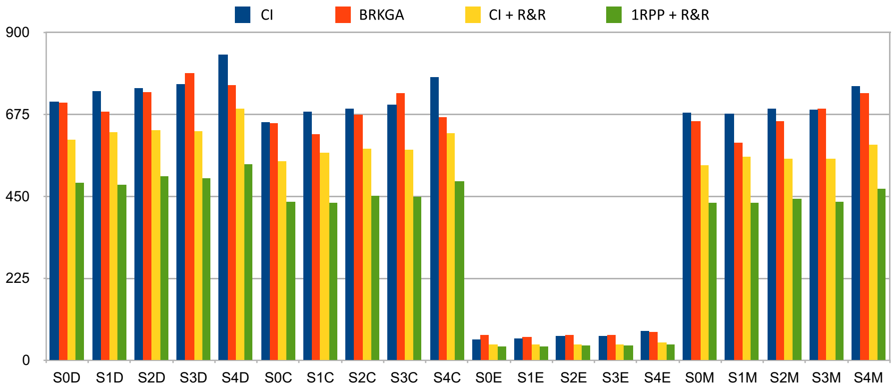


Fig. 5 Algorithmic performance with respect to the emissions KPI on the suburban instances

5.2 Alternative policies analysis

This section simulates the proposed alternative parcel delivery policies on real-world e-commerce delivery data. Due to confidentiality issues, only aggregated results are presented. The size of the real-world instances makes CI the most appropriate algorithm for simulating scenarios enabling to investigate the impact of ECO vehicles on parcel delivery (Sect. 5.2.1), the impact of a shift from home deliveries to collection

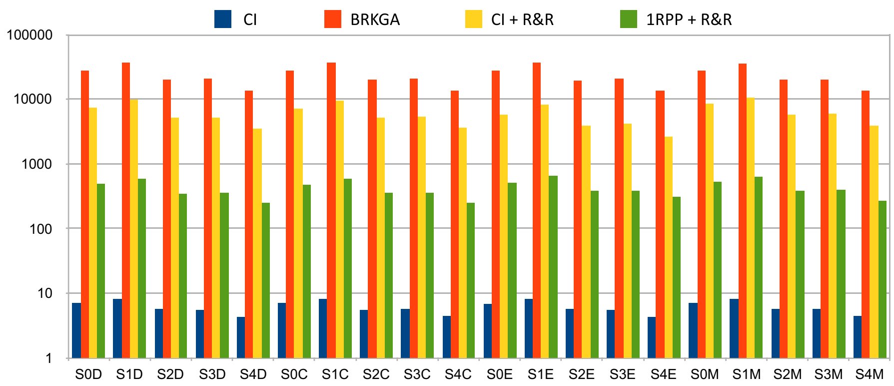


Fig. 6 Algorithm performance with respect to computation time

Table 3 Vehicle properties for the ECO-vehicle experiments

	Diesel	Diesel S/S	CNG S/S	E-single	E-double
Speed	30 km/h	30 km/h	30 km/h	30 km/h	30 km/h
Range[a]	300 km	300 km	300 km	140 km	112 km
Max route time	9 h	9 h	9 h	9 h	4 h
Routes per day	1	1	1	1	2
Start/Stop	No	Yes	Yes	Yes	Yes
CO_2 emission[b]	3140 g/l	3140 g/l	2532 g/kg	278 g/kWh	278 g/kWh

[a]Ranges for the Diesel, Diesel S/S, and CNG vehicles are adjusted to reflect the limits imposed by vehicle speed and maximum route time

[b]Electric vehicles do not produce emissions while driving, but the reported emissions are those corresponding to the production of the required electricity, assuming that the average values reported by the EU (European Commission 2011)

point retrievals (Sect. 5.2.2), and alternative delivery policies (Sect. 5.2.4). The instances employed to study the *regional carrier monopolies* (Sect. 5.2.3) are much smaller, which enables the application of the best performing algorithm in terms of quality, namely, 1RPP + R&R.

5.2.1 *Impact of ECO vehicles on parcel delivery*

Three types of fuel were considered for these experiments: diesel, CNG, and electricity (E). To enable an interesting comparison between the different fuel types and corresponding vehicles, drivers are assumed to have three primary tasks: load the van at the depot, deliver the parcels, and debrief at the depot (such as reporting undelivered or refused parcels). Vehicle characteristics are defined for each fuel type in Table 3 under the assumptions that the maximum working time for a parcel delivery driver is 10 h per day and the process of both loading and debriefing takes approximately 1 h in total.

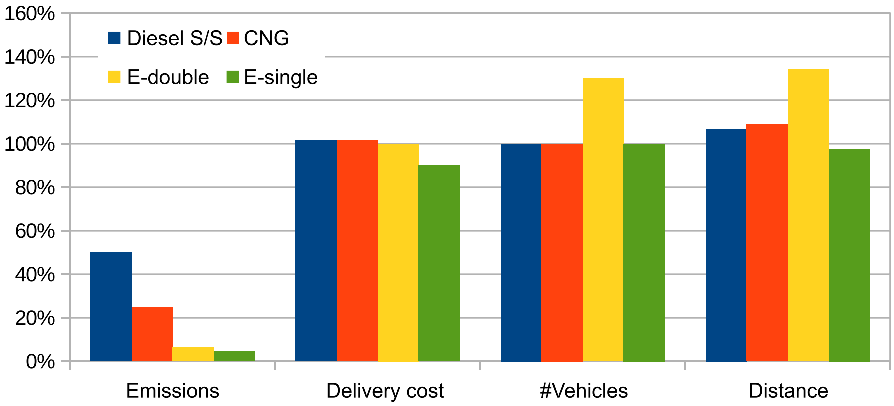


Fig. 7 Percentual gain (vertical) of employing ECO vehicles on the different KPIs (horizontal)

Two electric vehicle types are defined: E-single which has a maximum tour duration of 9 h, allowing for a single route per vehicle per day and an alternative E-double vehicle with a maximum tour duration of 4 h, resulting in two routes per vehicle per day. E-double vehicles employ quick chargers at the depot capable of charging the battery up to 80% in 1 h, thereby enabling the execution of up to two routes per day. The quick-charge duration is equivalent to the time required to debrief for the first route and load parcels for the second. Both CNG and E-vehicles employ start–stop technology, meaning that their engines are switched off and zero emissions temporarily occur, while the driver is outside the vehicle. Start–stop technology is optional for diesel vehicles, and therefore, a comparison is made between scenarios with and without start–stop technology.

The effect of employing ECO vehicles for parcel delivery is simulated for a large (sub)urban area, with the depot located at the edge of the city center. 47,000 parcels require delivery over a period of 2 months and the maximum distance between depot and parcel destination is 18 km.

All parcels are delivered by a standard diesel van unequipped with start–stop technology in the reference scenario and this is compared against scenarios employing ECO vehicles.

Figure 7 summarizes the results for ECO-vehicle simulations. The chart demonstrates how applying start–stop technology during parcel delivery results in considerable emission decreases. Applying start–stop technology has no significant influence on other KPIs. Fuel costs, for example, represent such a small cost share that the decrease in fuel consumption results in no significant total cost reduction. When switching to CNG vehicles, CO_2 emissions decrease even further, while total costs remain stable. Furthermore, NO_x emissions are practically reduced to zero. Switching to CNG vehicles may, therefore, prove ecologically worthwhile for carriers. When employing E-double vehicles performing two routes per day with quick-charge technology, small decreases in the cost KPI are noticeable. There are, however, 25% more vehicles required to deliver the parcels, rendering them undesirable from a practical and investment perspective. When considering the E-single vehicles, however, a

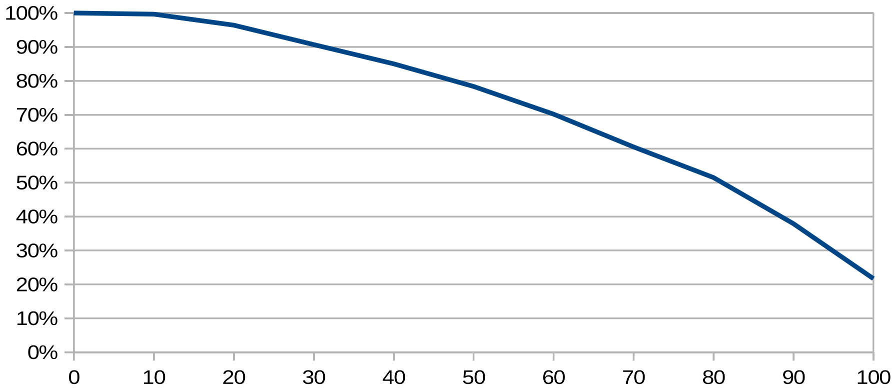


Fig. 8 Influence of the percentage of parcels delivered at collection points (horizontal) on emissions (vertical)

completely different result is obtained. The cost KPI is significantly reduced compared to the diesel van scenario and all parcels are delivered using an equal number of vehicles. Therefore, employing electric vehicles is both economically and ecologically worthwhile for carriers operating within urban environments.

5.2.2 Impact of a shift from home deliveries to collection point retrievals

Data concerning delivery parcels in an urban area over a period of 2 months was employed to accurately investigate the effects of transitioning from home deliveries to collection point retrievals. Approximately 28,000 parcels were delivered over this 2 month period with between 60 and 1000 delivered on any single day. Characteristics of the vehicles employed are those of a standard diesel van running at 30 km/h, as detailed in Table 3.

An existing network of 24 collection points was utilized with all original delivery addresses within 3 km of their collection point for the simulation. By contrast, all parcels are delivered to their original destination in the reference scenario. 10–100% of the parcels are randomly moved from their original destination to the nearest collection point.

Figure 8 illustrates the decrease in emissions when delivering varying percentages of parcels to collection points. Emission costs decrease by 0.3–78% when utilizing a dense collection point network. Internal KPIs (f_l, f_d and f_v) demonstrate a similar reduction, as indicated by Fig. 9.

It is noteworthy that the reimbursement of collection point personnel is not included in the cost computation and the actual cost decrease will, therefore, be somewhat lower.

5.2.3 Regional carrier monopolies: (sub)urban vs. rural

Two different regions were considered when simulating the effect of regional carrier monopolies. Region 1 is a medium-sized city and its surrounding suburban

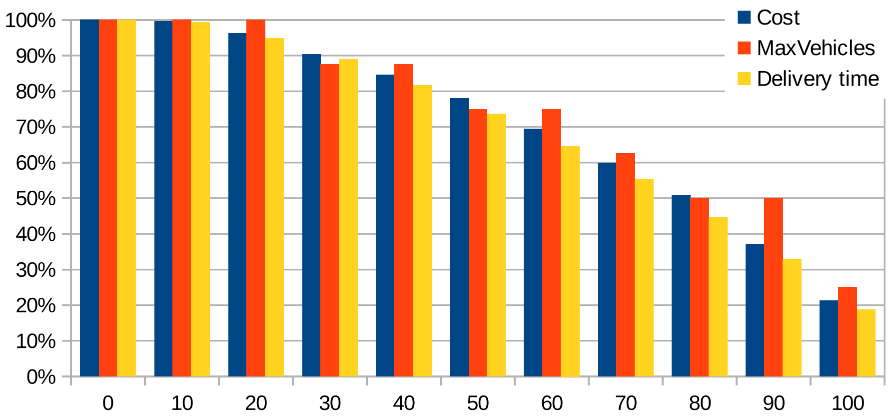


Fig. 9 Influence of the percentage of parcels delivered at collection points (horizontal) on three KPIs (vertical)

Table 4 Vehicle properties for the default diesel van

	City	Rural
Speed (diesel van)	30 km/h	50 km/h
Range	300 km	500 km
Max route time	10 h	
CO_2 emission	3140 g/l	
Stop duration	4 min	
MultiStop duration	0.4 min per parcel	

The vehicle's range is adjusted to reflect the speed limits and maximum route duration

environment with 25,000 parcels requiring delivery over a period of 1 month, corresponding to a high parcel density. Parcel and depot data from two carriers were obtained, while only depot information was obtained from a third carrier for this region. The first two carriers have depots at the edge of the considered region, whereas the third is centrally located. In the reference scenario, Carriers 1 and 2 deliver parcels from their respective depots. Characteristics of the vehicles employed are those of a standard diesel van running at 30 km/h ((Sub)urban) and 50 km/h (Rural), as described in Table 4, and the algorithm applied is 1RPP + R&R heuristic.

Figure 10 summarizes Region 1's results when all parcels are delivered by either Carrier 1, Carrier 2, or Carrier 3 in a monopoly scenario. Beware that all parcels' origins are assumed to be the monopoly holder's depot. Only one small advantage is to be made from assigning carrier monopolies in this type of dense region, with cost decreases of between 4 and 7%. All carriers' delivery routes appear to already be saturated and there is little advantage insofar as including additional parcels in their workload. Moving the depot from the region's edge to a central location (Carrier 3) results in greater KPI improvements, with a cost

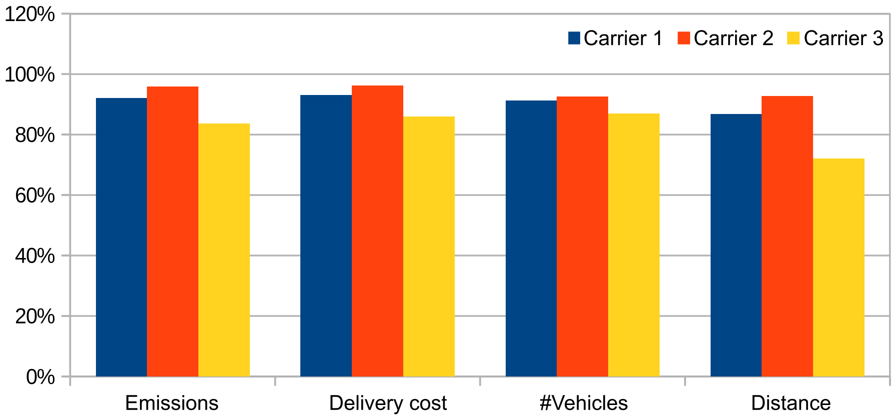


Fig. 10 Relative delivery costs in case of an urban carrier monopoly (either Carrier 1, 2, or 3), compared to the situation, where all three carriers have a share

decrease of 14%, mainly due to the decrease in distance traveled per parcel. It may, however, still be questioned whether this decrease in delivery cost sufficiently compensates for the probable increase in costs and complexity in the long run, since parcels must be redistributed outside current carrier logistic flows.

Region 2 is more rural with a total of 150 parcels requiring delivery over a period of 5 weeks, corresponding to a (very) low parcel density. Parcel and depot data were obtained from only one single major carrier operating in this region. For investigating the effect of multiple carriers in the region, the delivery data have been divided into five sets. Subsequently, these sets have been assigned to separate fictitious carriers, thus mimicking the effect of five carriers operating simultaneously within the region. All parcels are assumed to be delivered within 1 week, albeit on their original delivery day of the week. In the reference scenario, parcels are delivered by five carriers independently. Four different scenarios simulate the impact of a rural carrier monopoly. The resulting costs and emissions are compared against the reference scenario.

Characteristics of the employed vehicles are those of a standard diesel van running at 50 km/h, as described in Table 4. Given how rural regions demand long travel distances per parcel, these are valid assumptions when compared against the 30 km/h for (sub)urban regions.

Figure 11 summarizes the results of scenarios in which all activities of two, three, four, or five carriers are merged into a monopoly home delivery. The results are compared against the reference scenario, where all five carriers conduct their delivery share in the region.

By contrast to the results obtained in the (sub)urban region, the benefits of enforcing a regional carrier monopoly are considerable. Decreases in emissions, costs, required vehicles, and distance per parcel of up to 80% were observed, while the average route duration increased from 4h40 to almost 8 h, thereby highlighting the capability of operating far more efficient routes when under increasing density conditions.

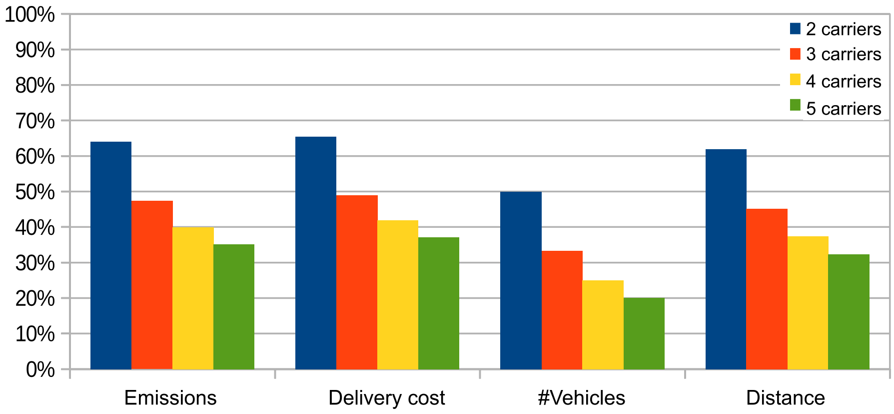


Fig. 11 Relative KPIs in a rural carrier scenario, where two, three, four, or five carriers are merged into a monopoly, reflecting increasing delivery density. The reference scenario reflects all five carriers having their share

Compared to urban deliveries, however, a monopolist's absolute rural delivery costs remain almost twice as high while the distance per parcel increases threefold, illustrating how low-density regions prove commercially challenging even under monopoly conditions.

5.2.4 Alternative delivery policies

Impact of reduced service time and start–stop technology

The following experiments concern simulating the impact of reducing the time required to deliver a parcel to its destination (service time) and the application of start–stop technology during parcel delivery. 47,000 parcels are delivered by the default diesel van with a service time of 4 min for the reference scenario. The simulation scenarios, meanwhile, consider service times of 1–5 min, and for each service time duration, the influence of applying start–stop technology is investigated.

Several interesting conclusions may be extrapolated from the results presented in Fig. 12. First and foremost, applying start–stop technology significantly reduces emissions during parcel delivery. Emissions are reduced by almost 40% for the base case (represented by the black line), where the service time is 4 min when switching off the engine during parcel delivery instead of letting the engine run idle (represented by the red line). Second, the graph clearly illustrates how service time must be halved to 2 min to obtain the same emission reductions as those obtained by applying start–stop technology when service time equals 4 min. Thus, from a purely ecological point of view, the application of start–stop technology represents a simple and immediate benefit, since it is much easier to implement than delivery policy changes which halve service time.

Figure 13, by contrast, visualizes the influence of start–stop technology and service time upon delivery costs. Given that the application of start–stop technology only affects total fuel cost (which is marginal compared to the driver's wage cost), it is unsurprising that the application of start–stop technology has only a negligible

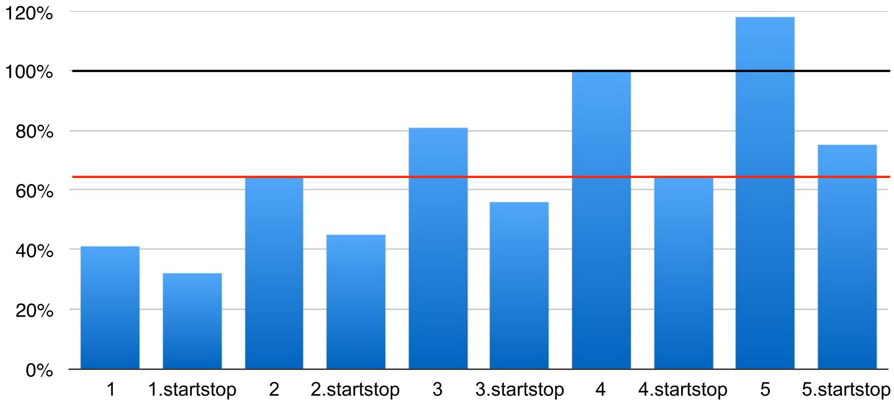


Fig. 12 Influence of service times [horizontal (min)] and start–stop technology (start–stop) on emissions (vertical). The reference scenario considers 4 min service time for standard vehicles without start–stop technology

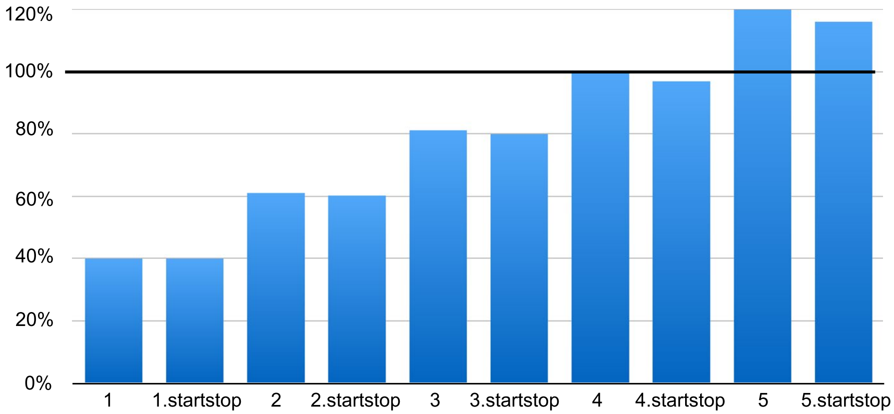


Fig. 13 Influence of service times [horizontal (min)] and start–stop technology (start–stop) on delivery cost (vertical). The reference scenario considers 4 min service time for the standard vehicles without start–stop technology

influence upon delivery costs. Therefore, from an economic perspective, it may be a difficult decision concerning whether or not investing in additional start–stop technology for new vehicles is worthwhile. Much greater cost reductions are obtained by reducing service time. Indeed, with high driver wage costs, any reduction in service time should incur significant delivery cost savings. These results demonstrate the need to further investigate the effects on service times by reducing parcel sizes and thereby increasing the percentage of parcels deliverable by mailbox.

Impact of increased time windows

The following experiments simulate the impact of increasing time windows for parcel delivery in an urban environment. Default diesel vans with a 4 min service time are employed to deliver over 47,000 parcels. The simulation investigates the impact of lengthening parcel delivery time windows from 1 to 4 days for 20, 40, and 60% of the parcels.

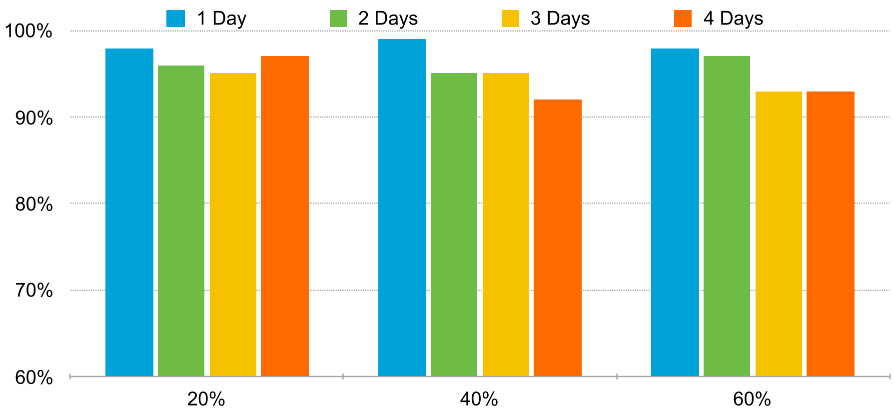


Fig. 14 Impact of increased delivery time windows on emissions. The horizontal axis indicates the portion of deliveries with increased time windows and the vertical axis presents relative emissions. The reference scenario indicates emissions for the original time windows

Figure 14 presents the results, where the horizontal axis corresponds to the three scenario categories (20, 40, and 60%) and the vertical axis details the level of emissions relative to the reference scenario (no extended time windows). The figure illustrates how increasing time windows does not yield the expected benefits. Indeed, increasing the time windows for 60% of the parcels by 4 days only results in emission decreases of 7%. In addition, a time window increase for 20% of the parcels by 2, 3, or 4 days result in similar emission decreases. A careful analysis of the results revealed that the real routes are densely loaded with deliveries. Regardless of any time window flexibilities, the most restrictive constraint appears to be the drivers' working time limits.

5.3 Discussion and insights

This paper's primary objective was to investigate the most profitable mode of e-commerce delivery operations, and it sought to reduce CO_2 emissions while satisfying customer service expectations. Computational experiments provided several insights which may be summarized as follows:

1. Contrary to intuition, regional carrier monopolies do not increase delivery efficiency, except in regions with very low parcel density.
2. Delivering parcels to a collection point instead of customers' homes significantly decreases both external (emissions) and internal costs (delivery cost, service time, fleet size). Moreover, customers collect their order at a delivery point whenever it proves convenient. This represents an indirect benefit for the transporter (no additional waiting times, no failed deliveries).
3. Significant benefits are obtained in all scenarios when the percentage of *bundled* deliveries is increased. Indeed, the number of orders requiring delivery to one point does not linearly increase service time at this destination.

4. Reducing delivery duration has the greatest impact on total cost, as expected, since it shortens the drivers' working time. For instance, if a customer is not at home, the driver must first wait for some time before writing a delivery notice.
5. Extending time windows does not yield the expected benefit, the primary reason being that most tours are saturated and cost reductions are marginal when compared against driver costs or those generated by to-the-door delivery.

6 Conclusion

The paper proposed a general optimization approach to the e-commerce delivery problem, enabling the assessment of various operational delivery policies on both costs and emissions. A mixed integer programming formulation, heuristic approaches, and several delivery policies were presented. Computational results were obtained by applying the presented heuristics to a selection of anonymized real-world data gathered from e-commerce delivery transporters.

Interestingly, experimental results often proved counter-intuitive. For example, while one might assume that extending delivery time windows would reduce both costs and emissions, results indicate that such relaxations result in little or no profit. Given high personnel costs, one would have also assumed that reducing the driving time would be beneficial. Instead, it appears that, especially in urban areas, reducing delivery time potentially contributes more significantly towards cost and emission reductions than reducing the actual driving time. Results reveal how emission costs are decreased by up to 78% when utilizing a dense collection point network and by up to 80% when enforcing a regional carrier monopoly in rural areas. Another important observation is that switching off vehicle engines during individual parcel delivery reduces the environmental impact considerably.

Several interesting avenues exist for future research. Recently, many companies in the United States and India have begun implementing a *crowd-shipping* strategy (Archetti et al 2016). By employing crowd-shipping, distributors ask customers who are collecting their orders to deliver those of other customers on their return journey in exchange for certain incentives. From a policy point of view, the environmental impact of integrating crowd-shipping into policies such as delivering to collection points or *carrier bundling* on home deliveries is worth exploring. This paper researches the impact of a few new policies, but many more remain to be investigated. Other research directions may focus on the realistic modeling of certain vehicle processes, such as energy consumption or CO_2 emissions. The vehicles' capacity constraints may represent yet another important issue that should be further investigated.

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Appendix

See Tables 5, 6, 7.

Table 5 Comparison of CI, BRKGA and R&R over rural instances

Ins.	VT	#P	CI					BRKGA					CI + R&R					1RPP + R&R				
			Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time
R0D	D	17	13.50	4332.34	15.52	1.00	0.02	13.50	4332.34	15.46	1.00	41.57	13.50	4332.34	15.52	1.00	1.01	13.50	4332.34	15.52	1.00	0.80
R1D	D	76	5.22	1772.92	6.59	2.00	0.03	4.73	1622.12	6.02	2.00	516.46	4.68	1605.67	6.02	2.00	5.39	4.67	1605.46	6.01	2.00	3.99
R2D	D	5	25.23	7849.71	27.49	1.00	0.01	25.23	7849.71	27.46	1.00	3.05	25.23	7849.71	27.49	1.00	0.46	25.23	7849.71	27.49	1.00	0.30
R3D	D	25	5.85	1944.14	7.13	1.00	0.01	5.81	1932.90	7.05	1.00	43.68	5.85	1944.14	7.13	1.00	0.87	5.86	1947.95	7.15	1.00	0.90
R4D	D	10	13.02	4209.88	15.15	1.00	0.01	13.02	4209.88	15.09	1.00	16.38	13.02	4209.88	15.15	1.00	0.60	13.02	4209.88	15.15	1.00	0.59
R5D	D	6	23.69	7444.99	26.26	1.00	0.01	23.69	7444.99	26.21	1.00	5.33	23.69	7444.99	26.26	1.00	0.47	24.39	7659.40	27.01	1.00	0.37
R6D	D	5	31.57	9888.54	34.81	1.00	0.01	31.57	9888.54	34.74	1.00	5.69	31.57	9888.54	34.81	1.00	0.47	31.57	9888.54	34.81	1.00	0.36
R7D	D	9	12.50	3908.77	13.74	1.00	0.01	12.50	3908.77	13.72	1.00	2.80	12.50	3908.77	13.74	1.00	0.39	12.50	3908.77	13.74	1.00	0.27
R8D	D	7	28.60	8959.81	31.54	1.00	0.01	28.60	8959.81	31.48	1.00	7.53	28.60	8959.81	31.54	1.00	0.49	28.60	8959.81	31.54	1.00	0.42
R9D	D	3	61.19	19,009.47	66.50	1.00	0.01	61.19	19,009.47	66.42	1.00	4.58	61.19	19,009.47	66.50	1.00	0.44	61.19	19,009.47	66.50	1.00	0.32
R10D	D	13	11.61	3674.56	13.03	1.00	0.01	11.59	3668.66	12.98	1.00	8.56	11.59	3668.66	13.01	1.00	0.49	11.59	3668.66	13.01	1.00	0.42
R11D	D	18	8.93	2896.05	10.45	1.00	0.01	8.90	2887.03	10.37	1.00	27.64	8.93	2896.05	10.45	1.00	0.68	8.94	2898.95	10.46	1.00	0.71
R12D	D	20	7.79	2474.48	8.80	1.00	0.01	7.79	2474.48	8.77	1.00	7.96	7.79	2474.48	8.80	1.00	0.50	7.79	2474.48	8.80	1.00	0.41
R13D	D	41	4.59	1485.41	5.35	1.00	0.01	4.09	1332.25	4.80	1.00	25.49	4.13	1345.56	4.87	1.00	0.61	4.12	1342.48	4.86	1.00	0.63
R14D	D	9	13.51	4381.35	15.80	1.00	0.01	13.51	4381.21	15.73	1.00	15.63	13.51	4381.21	15.80	1.00	0.60	13.51	4381.21	15.80	1.00	0.59
R15D	D	14	13.89	4470.86	16.05	1.00	0.01	13.89	4470.86	15.98	1.00	27.62	13.89	4470.86	16.05	1.00	0.71	14.01	4508.38	16.18	1.00	0.74
R0C	C	17	13.50	4162.68	15.85	1.00	0.01	13.50	4162.68	15.79	1.00	42.84	13.50	4162.68	15.85	1.00	0.76	13.50	4162.68	15.85	1.00	0.80
R1C	C	76	5.22	1688.50	6.72	2.00	0.03	4.73	1542.48	6.14	2.00	411.63	4.68	1526.55	6.12	2.00	5.29	4.66	1522.07	6.11	2.00	4.10
R2C	C	5	25.23	7580.35	28.12	1.00	0.01	25.23	7580.35	28.09	1.00	2.80	25.23	7580.35	28.12	1.00	0.46	25.23	7580.35	28.12	1.00	0.27
R3C	C	25	5.85	1857.63	7.27	1.00	0.01	5.81	1846.74	7.19	1.00	43.68	5.85	1857.63	7.27	1.00	0.82	5.85	1859.13	7.28	1.00	0.89
R4C	C	1	13.02	4040.41	15.47	1.00	0.01	13.02	4040.41	15.41	1.00	16.14	13.02	4040.41	15.47	1.00	0.58	13.02	4040.41	15.47	1.00	0.59
R5C	C	6	23.69	7178.01	26.85	1.00	0.01	23.69	7178.01	26.80	1.00	5.34	23.69	7178.01	26.85	1.00	0.50	24.39	7385.61	27.61	1.00	0.37
R6C	C	5	31.57	9538.72	35.59	1.00	0.01	31.57	9538.72	35.53	1.00	5.74	31.57	9538.72	35.59	1.00	0.47	31.57	9538.72	35.59	1.00	0.39
R7C	C	9	12.50	3771.54	14.05	1.00	0.01	12.50	3771.54	14.03	1.00	3.78	12.50	3771.54	14.05	1.00	0.40	12.50	3771.54	14.05	1.00	0.29
R8C	C	7	28.60	8642.85	32.24	1.00	0.01	28.60	8642.85	32.19	1.00	7.88	28.60	8642.85	32.24	1.00	0.49	28.60	8642.85	32.24	1.00	0.42

Table 5 (continued)

Ins.	VT	#P	CI					BRKGA					CI + R&R					1RPP + R&R				
			Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time
R9C	C	3	61.19	18,362.11	68.02	1.00	0.01	61.19	18,362.11	67.95	1.00	4.52	61.19	18,362.11	68.02	1.00	0.45	61.19	18,362.11	68.02	1.00	0.31
R10C	C	13	11.61	3538.39	13.32	1.00	0.01	11.59	3532.69	13.27	1.00	8.57	11.59	3532.69	13.30	1.00	0.50	11.59	3532.69	13.30	1.00	0.41
R11C	C	18	8.93	2777.90	10.67	1.00	0.01	8.90	2769.17	10.59	1.00	27.64	8.93	2777.90	10.67	1.00	0.69	8.94	2781.52	10.68	1.00	0.69
R12C	C	20	7.79	2381.71	8.99	1.00	0.01	7.79	2381.71	8.96	1.00	8.39	7.79	2381.71	8.99	1.00	0.51	7.79	2381.71	8.99	1.00	0.43
R13C	C	41	4.59	1425.26	5.46	1.00	0.01	4.09	1276.96	4.90	1.00	27.32	4.13	1289.84	4.97	1.00	0.62	4.13	1288.26	4.96	1.00	0.64
R14C	C	9	13.51	4202.95	16.13	1.00	0.01	13.51	4202.82	16.07	1.00	14.32	13.51	4202.82	16.13	1.00	0.58	13.51	4202.82	16.13	1.00	0.58
R15C	C	14	13.89	4293.66	16.38	1.00	0.01	13.89	4293.66	16.33	1.00	27.50	13.89	4293.66	16.38	1.00	0.71	14.00	4325.80	16.50	1.00	0.75
R0M	M	17	13.50	4162.68	15.85	1.00	0.02	13.50	4162.68	15.79	1.00	25.02	13.50	4162.68	15.85	1.00	0.83	18.15	4054.08	20.77	1.90	0.87
R1M	M	76	7.56	1637.95	9.19	4.00	0.04	9.08	991.59	10.74	5.00	302.54	4.70	1068.98	6.11	2.00	2.06	5.77	1032.59	7.24	2.90	4.06
R2M	M	5	25.23	1096.96	27.68	1.00	0.01	25.23	1096.96	27.68	1.00	2.90	25.23	1096.96	27.68	1.00	0.72	25.23	1096.96	27.68	1.00	0.34
R3M	M	25	13.74	597.46	15.57	3.00	0.02	10.37	450.74	11.97	2.00	28.89	10.37	450.74	11.97	2.00	0.91	10.37	450.74	11.97	2.00	1.00
R4M	M	10	21.67	942.23	24.44	2.00	0.02	21.67	942.23	24.44	2.00	12.60	21.67	942.23	24.44	2.00	0.82	21.67	942.23	24.44	2.00	0.67
R5M	M	6	32.29	1404.25	35.61	2.00	0.01	32.29	1404.25	35.61	2.00	5.33	32.29	1404.25	35.61	2.00	0.80	32.29	1404.25	35.61	2.00	0.41
R6M	M	5	55.28	9878.54	60.85	2.00	0.01	31.57	9538.72	35.53	1.00	5.45	31.57	9538.72	35.59	1.00	0.76	31.57	9538.72	35.59	1.00	0.41
R7M	M	9	12.50	543.52	13.83	1.00	0.01	12.50	543.52	13.83	1.00	2.79	12.50	543.52	13.83	1.00	0.72	12.50	543.52	13.83	1.00	0.33
R8M	M	7	28.60	8642.85	32.24	1.00	0.01	28.60	8642.85	32.19	1.00	6.90	28.60	8642.85	32.24	1.00	0.78	28.60	8642.85	32.24	1.00	0.49
R9M	M	3	61.19	18,362.11	68.02	1.00	0.01	61.19	18,362.11	67.95	1.00	4.08	61.19	18,362.11	68.02	1.00	0.74	61.19	18,362.11	68.02	1.00	0.44
R10M	M	13	18.90	821.73	20.90	2.00	0.01	17.39	756.01	19.28	2.00	7.39	17.39	756.01	19.28	2.00	0.81	17.39	756.01	19.28	2.00	0.52
R11M	M	18	20.80	2798.91	23.30	3.00	0.01	19.98	2967.00	22.40	3.00	18.38	14.43	2611.89	16.50	2.00	0.84	13.42	2628.91	15.43	1.90	0.75
R12M	M	20	19.93	2769.90	21.94	3.00	0.01	7.79	2381.71	8.96	1.00	6.70	7.79	2381.71	8.99	1.00	0.80	7.79	2381.71	8.99	1.00	0.48
R13M	M	41	9.30	1315.60	10.47	3.00	0.01	4.09	1276.96	4.90	4.00	16.88	6.39	1264.30	7.36	2.00	0.84	6.38	1264.10	7.36	2.00	0.69
R14M	M	9	13.51	587.67	15.85	1.00	0.01	13.51	587.65	15.85	1.00	14.87	13.51	587.65	15.85	1.00	0.83	13.51	587.65	15.85	1.00	0.65
R15M	M	14	13.89	4293.66	16.38	1.00	0.02	13.89	4293.66	16.33	2.00	20.37	13.89	4293.66	16.38	1.00	0.84	20.47	4137.62	23.37	2.00	0.79

Table 6 Comparison of CI, BRKGA and R&R over urban instances

Ins.	VT	#P	CI					BRKGA					CI + R&R					1RPP + R&R				
			Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time
U0D	D	837	0.27	257.79	1.35	5.00	0.28	0.19	233.41	1.21	5.00	3478.22	0.25	251.38	1.33	5.00	4.62	0.18	229.05	1.25	5.10	4.11
U1D	D	681	0.28	250.67	1.30	4.00	0.17	0.20	227.44	1.17	4.00	2429.35	0.25	240.65	1.27	4.00	1.84	0.19	223.13	1.21	4.10	2.54
U2D	D	886	0.24	228.36	1.20	5.00	0.22	0.17	208.09	1.08	5.00	2857.47	0.22	221.72	1.18	4.90	3.91	0.16	203.28	1.11	4.50	3.51
U3D	D	612	0.00	0.00	0.00	0.00	0.00	0.22	249.49	1.29	4.00	2527.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U4D	D	594	0.00	0.00	0.00	0.00	0.00	0.23	244.92	1.26	4.00	1682.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U0C	C	837	0.27	221.42	1.35	5.00	0.26	0.20	199.33	1.22	5.00	3111.08	0.25	214.62	1.33	5.00	4.33	0.18	193.52	1.25	5.00	4.11
U1C	C	681	0.28	215.98	1.30	4.00	0.18	0.21	193.99	1.18	4.00	2131.97	0.24	204.94	1.26	4.00	1.68	0.19	189.44	1.21	4.00	2.49
U2C	C	886	0.24	196.06	1.20	5.00	0.23	0.18	178.62	1.09	5.00	2489.18	0.22	188.83	1.17	4.80	4.22	0.16	171.57	1.11	4.30	3.38
U3C	C	612	0.00	0.00	0.00	0.00	0.00	0.23	213.91	1.30	4.00	2142.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U4C	C	594	0.00	0.00	0.00	0.00	0.00	0.23	209.13	1.26	4.00	1723.39	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U0E	E	837	0.27	11.89	1.30	5.00	0.26	0.20	8.50	1.22	5.00	2744.44	0.25	11.05	1.28	5.00	4.61	0.18	7.75	1.20	5.00	4.10
U1E	E	681	0.28	12.15	1.25	4.00	0.17	0.20	8.88	1.17	4.00	1764.47	0.24	10.60	1.22	4.00	1.85	0.19	8.22	1.16	4.00	2.50
U2E	E	886	0.17	7.32	0.81	3.50	0.15	0.18	7.77	1.09	5.00	2132.38	0.15	6.53	0.79	3.30	2.76	0.11	4.84	0.75	3.10	2.44
U3E	E	612	0.00	0.00	0.00	0.00	0.00	0.22	9.73	1.29	4.00	1869.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U4E	E	594	0.00	0.00	0.00	0.00	0.00	0.22	9.71	1.26	4.00	1471.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U0M	M	837	0.27	11.89	1.30	5.00	0.26	0.19	8.32	1.21	5.00	2772.98	0.26	11.29	1.29	5.00	2.68	0.30	13.09	1.33	5.00	4.47
U1M	M	681	0.28	12.15	1.25	4.00	0.19	0.20	8.75	1.17	4.00	1765.54	0.25	10.78	1.22	4.00	1.28	0.24	10.86	1.22	4.10	2.73
U2M	M	886	0.00	0.00	0.00	0.00	0.00	0.17	7.45	1.08	5.00	2183.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U3M	M	612	0.00	0.00	0.00	0.00	0.00	0.22	9.67	1.29	4.00	1838.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
U4M	M	594	0.00	0.00	0.00	0.00	0.00	0.23	9.79	1.26	4.00	1439.30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 7 Comparison of CI, BRKGA and R&R over suburban instances

Ins.	VT	#P	CI					BRKGA					CI + R&R					1RPP + R&R				
			Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time	Dis.	Em.	€	#R	Time
S0D	D	5194	1.66	709.47	2.99	55.00	7.08	1.65	706.39	2.92	53.40	27,734.38	1.32	606.60	2.63	49.50	7476.69	0.94	488.61	2.22	42.90	500.09
S1D	D	5529	1.75	738.82	3.10	61.00	8.20	1.56	683.35	2.84	56.20	37,197.88	1.38	626.13	2.71	54.00	9767.92	0.91	481.87	2.21	45.60	588.57
S2D	D	4466	1.76	747.23	3.14	50.00	5.70	1.73	737.07	3.04	52.80	19,869.71	1.38	631.93	2.74	44.20	5284.41	0.97	504.93	2.30	38.10	350.95
S3D	D	4580	1.81	758.25	3.16	51.00	5.64	1.91	787.92	3.20	53.40	20,802.09	1.39	628.63	2.71	45.00	5277.74	0.96	499.14	2.27	38.60	356.42
S4D	D	3743	2.04	841.02	3.48	46.00	4.37	1.76	755.36	3.12	55.00	13,786.34	1.56	692.25	2.96	40.10	3478.97	1.05	538.26	2.43	33.90	249.27
S0C	C	5194	1.66	654.27	3.02	55.00	7.06	1.65	650.88	2.95	55.00	27,615.20	1.30	547.16	2.63	49.10	7286.01	0.92	435.79	2.22	42.60	486.44
S1C	C	5529	1.75	682.27	3.13	61.00	8.21	1.53	619.52	2.85	55.80	37,097.37	1.37	569.92	2.72	53.80	9624.12	0.90	432.80	2.22	45.40	598.19
S2C	C	4466	1.76	689.81	3.17	50.00	5.66	1.70	673.01	3.05	55.40	19,866.75	1.39	579.91	2.77	44.20	5195.64	0.95	450.62	2.29	37.90	358.38
S3C	C	4580	1.81	701.12	3.20	51.00	5.76	1.91	731.66	3.26	53.20	20,826.72	1.39	577.65	2.75	45.00	5482.66	0.96	448.30	2.27	38.50	356.38
S4C	C	3743	2.04	779.39	3.52	46.00	4.46	1.67	668.55	3.06	52.80	13,565.85	1.51	623.17	2.95	39.50	3666.40	1.07	490.33	2.46	34.20	251.55
S0E	E	5194	1.35	58.56	2.61	56.00	7.00	1.57	68.28	2.85	56.40	27,729.59	1.00	43.49	2.24	44.40	5735.09	0.91	39.49	2.14	43.00	509.56
S1E	E	5529	1.37	59.69	2.65	60.00	8.15	1.49	64.58	2.77	64.20	37,192.35	1.01	43.95	2.26	47.60	8171.89	0.88	38.30	2.12	45.30	654.86
S2E	E	4466	1.55	67.22	2.86	54.00	5.79	1.57	68.49	2.89	55.40	19,764.83	1.03	44.95	2.31	39.40	3945.61	0.94	40.68	2.21	38.00	392.21
S3E	E	4580	1.54	66.85	2.83	55.00	5.67	1.56	67.92	2.85	55.00	20,578.25	1.02	44.27	2.27	39.70	4226.97	0.93	40.26	2.17	38.30	385.85
S4E	E	3743	1.83	79.39	3.20	53.00	4.33	1.76	76.47	3.13	56.20	13,491.12	1.11	48.34	2.44	34.90	2616.27	1.02	44.45	2.34	33.90	306.83
S0M	M	5194	1.73	680.43	3.07	58.00	7.26	1.71	656.64	3.03	59.00	27,314.66	1.30	535.74	2.61	49.30	8439.64	0.96	431.93	2.25	43.40	529.60
S1M	M	5529	1.71	675.85	3.06	61.00	8.29	1.48	596.70	2.82	57.80	35,482.25	1.36	559.40	2.68	53.70	10,676.80	0.94	432.76	2.24	46.10	626.92
S2M	M	4466	1.80	692.11	3.18	51.00	5.75	1.68	657.72	3.05	54.80	19,850.22	1.37	552.34	2.72	44.10	5819.49	1.02	444.65	2.35	38.80	390.00
S3M	M	4580	1.78	686.82	3.14	52.00	5.71	1.81	690.41	3.16	55.20	20,042.94	1.38	554.23	2.71	44.90	5994.38	0.99	434.21	2.29	39.00	402.42
S4M	M	3743	2.01	753.29	3.45	47.00	4.48	1.92	734.30	3.35	55.00	13,667.59	1.52	591.20	2.92	39.60	3916.82	1.12	472.44	2.50	34.90	267.18

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