Multi-Objective Vehicle Routing Problem Applied to Large Scale Post Office Deliveries

Luis A. A. Meira\(^a,\)\(^,^\) Paulo S. Martins\(^a,\) Mauro Menzori\(^a,\) Guilherme A. Zeni\(^a\)

\(^a\)School of Technology, University of Campinas, Pascoal Marmon, 1888, Limeira, SP, Brazil

Abstract

The number of optimization techniques in the combinatorial domain is large and diversified. Nevertheless, real-world based benchmarks for testing algorithms are few. This work creates an extensible real-world mail delivery benchmark to the Vehicle Routing Problem (VRP) in a planar graph embedded in the 2D Euclidean space. Such problem is multi-objective on a roadmap with up to 25 vehicles and 30,000 deliveries per day. Each instance models one generic day of mail delivery, allowing both comparison and validation of optimization algorithms for routing problems. The benchmark may be extended to model other scenarios.

Keywords: Routing, Large scale optimization, Multi-objective optimization, Logistics, OR in service industries.

\(^*\)Corresponding author
Email addresses: meira@ft.unicamp.br (Luis A. A. Meira), paulo@ft.unicamp.br (Paulo S. Martins), mauro@ft.unicamp.br (Mauro Menzori), g146284@dac.unicamp.br (Guilherme A. Zeni)
URL: http://www.ft.unicamp.br/~meira (Luis A. A. Meira)
1. Introduction

Benchmarks are found in various fields of science, such as geology (Correia et al., 2015), economics (Jorion, 1997), and climatology (Tol, 2002), among other areas. They play a central role in computer science, e.g., in image processing (du Buf et al., 1990; Krizhevsky et al., 2012; Huang et al., 2007), hardware performance (Che et al., 2009), and optimization (Reinelt, 1991; Kolisch & Sprecher, 1997; Burkard et al., 1997).

Within the context of optimization, Johnson (2002) divided algorithm analysis in three approaches: the worst-case, the average-case, and the experimental analysis. Regarding experimental papers, he identifies four cases: (i) solving a real problem; (ii) providing evidence that one algorithm is superior to others; (iii) better understanding a problem; and (iv) studying the average case. He proposes the use of well-established benchmarks to provide evidence of the superiority of an algorithm (item ii). Such papers are called horse race papers.

Johnson highlights that reproducibility and comparability are essential aspects of any experimental paper. The author mentions the difficulty in justifying experiments on problems with no direct application. Such problems have no real instances and the researcher is forced to generate the data in a vacuum.

Our work deals with a variant of the Vehicle Routing Problem (VRP) based on a real mail delivery case in the city of Artur Nogueira. The post office receives thousands of mail items to be delivered on a daily basis. Such mail is distributed to a set of 15-25 mail carriers for on-foot delivery. Each mail carrier is modeled as a vehicle and each delivery point is a customer. This variant is named here as Post Office Deliveries VRP (PostVRP).
Domain experts indicate that the PostVRP has three main objective functions to be minimized (while maintaining the feasibility of the solutions): (i) route length; (ii) unfairness, measured as the workload (i.e. route length) variance among the mail carriers; and (iii) number of mail carriers.

The PostVRP considers uncapacitated vehicles and constrained route length. Each mail carrier is allowed to carry a maximum load from 8 to 10 kg. A support truck restocks the mail carriers turning their capacities unlimited. Each mail carrier must follow a 6-to-8-hour working day, which implies a maximum capacity for the route length.

A limited route length is a constraint that models several real-world cases: A helicopter has a route length limited by the capacity of its fuel tank. Workers, in general, have a time window to operate the vehicle, which likewise limits the length of the route.

**Contribution:** This work presents a case study modeled in a Brazilian city located at 22°34′22″S 47°10′22″W. The proposed benchmark contains up to 30,000 customers. We make available the benchmark tool so that it is possible to create new arbitrarily large instances. The methodology can be applied to other cities as well as to other VRP variants.

The remainder of this paper is organized as follows: the background and review of relevant work is provided in Section 2; in Section 3 we introduce the notation and definitions; Section 4 presents the model; and Section 5 addresses a real-world PostVRP benchmark case. Finally, we summarize and conclude in Section 6.
2. Literature review

One of the first references to the VRP dates back to 1959 (Dantzig & Ramser, 1959), under the name Truck Dispatching Problem, a generalization of the Traveler Salesman Problem (TSP). The term VRP was first seen in the paper Christofides (1976). Christofides defines VRP as a generic name, given to a class of problems that involves the visit of “customers” using vehicles.

Real world aspects may impose variants to the problem. For example, the Capacitated-VRP (CVRP) considers a limit to the vehicle capacity (Fukasawa et al., 2006), the VRP with Time Windows (VRPTW) accounts for the delivery time windows (Kallehauge et al., 2005), and the Multi-Depot VRP (MDVRP) extends the number of depots (Renaud et al., 1996). Other variants may be easily found in the literature.

Reinelt (1991) created a benchmark for the TSP known as TSPLib. In his work, he consolidated non-solved instances from 20 distinct papers. His repository, named TSPLIB95 (Reinelt, 1995), has instances of both the symmetric and the asymmetric Traveling Salesman Problem (TSP/aTSP) as well as three related problems: (i) CVRP; (ii) Sequential Ordered Problem (SOP); and (iii) Hamiltonian Cycle Problem (HCP).

The number of instances is 113, 19, 16, 41, 9 for TSP, aTSP, CVRP, SOP, and HCP, respectively. The number of vertices varies from 14 to 85,900 for the TSP, 17 to 443 for the aTSP, 7 to 262 for the CVRP, 7 to 378 for the SOP, and from 1,000 to 5,000 for the HCP.

The optimum of all TSPLib instances was finally achieved in 2007, after sixteen years of notable progress in algorithm development. The optimum of the d15112 instance was found in 2001 (Applegate et al., 2011). This in-
stance contains 15,112 German cities and it required 22.6 years of processing split across 110 500 MHz processors (Cook, 2016). The instance pla33810 was solved in March 2004 (Applegate et al., 2011). The pla33810 instance represents a printed circuit board with 33,810 nodes and it was solved in 15.7 years of processing (Espinoza, 2006). The last instance of the TSPLib, called pla85900, was solved in 2006 (Applegate et al., 2011). This instance contains 85,900 nodes representing a VLSI application.

Solomon (1987) created a benchmark for the VRPTW in 1987. It is composed of 56 instances partitioned in six sets. The number of customers is 100 in all instances. The vehicle has a fixed capacity and the customers have an integer demand. The number of vehicles is not fixed: it derives from the fact that capacity is limited. Under this viewpoint, this can be considered a multi-objective problem. It aims to minimize the route and the number of vehicles.

The first optimum solution was published by Kohl et al. (1999). Chabrier (2006) solved 17 open instances in the benchmark. Amini et al. (2010) obtained solutions very close to the optimum, considering only the first 25 customers. In July 2015, 28 years after having launched the benchmark, Jawarneh & Abdullah (2015) published a Bee Colony Optimization metaheuristic. Such algorithm reached 11 new best results in Solomon’s VRPTW instances. It is surprising that such small instances present a quite complex internal structure to be optimized. Fig. 1 shows a Solomon’s instance composed of 100 customers and a given solution considering three vehicles.

Regardless of their complexity, the TSPLib and the Solomon benchmarks have a number of customers between 100 and 262 for the VRP, which is currently a small value. Gehring & Homberger (1999) extended the Solomons instances, thus creating a benchmark for the VRPTW with the number of
For the CVRP, ABEFMP is a largely used set of instances, in which Augerat et al. (1995) proposed the A, B, P classes in 1995, and (Christofides & Eilon, 1969; Fisher, 1994; Christofides, 1979) proposed the E, F, M classes in 1969, 1994 and 1979, respectively. In their benchmark, the number of customers varies from 13 to 200, and the number of vehicles varies from 2 to 17.

Fukasawa et al. (2006) and Contardo & Martinelli (2014), among others, obtained the optimum in different ABEFMP instances. Pecin et al. (2014) found the optimum solution for the last unsolved instance, named $M-n151-k12$, 35 years after its presentation by Christofides (1979). Despite that, most of those instances are very simple to solve nowadays.

Golden et al. (1998) proposed new instances for the CVRP. It is a set of 20 instances, with the number of customers varying from 240 to 483. Such benchmark remains entertaining, because most of its instances still do
not have an optimum established (Uchoa et al., 2017a). Li et al. (2005) created a set of instances with the number of customers between 560 and 1200. Currently, no optimum has been found for any of the instances (Uchoa et al., 2017a).

Uchoa et al. (2017a) created the CVRPLib where they consolidated the CVRP instances of (Augerat et al., 1995; Christofides & Eilon, 1969; Christofides, 1979; Fisher, 1994; Golden et al., 1998; Li et al., 2005). In addition, Uchoa et al. (2017b) generated new instances with the number of customers between 100 and 1,000. Their work indicates the lack of well-established challenging benchmarks for the VRP.

Uchoa et al. also highlight the fact that benchmarks are artificially created. Solomon and Uchoa et al. generated their own instances using random points. In the ABEFMP benchmark, some random instances are generated and other instances represent real problems. However, in all the instances the customers are points in the Euclidean space. The instances Golden et al. (1998) and Li et al. (2005) are artificial as well.

3. Notation and definition

Consider a set of elements $S$ where a depot is a special element $\pi \in S$. This work does not address multiple-depot variants to the VRP. The set of customers is defined by $C = S \setminus \{\pi\}$ and the number of customers is denoted by $n$, where $C = \{c_1, \ldots, c_n\}$. The number of vehicles in the fleet is represented by $k \in \mathbb{N}$. The value $k$ is traditionally considered a constant, but it is possible to define variants to VRP where $k$ is variable. Let $w : S \times S \to \mathbb{N}$ be the cost between any two elements in $S$. Let $S(C, k) = (c_1, \ldots, c_n, \pi, \ldots, \pi)$. This sequence is created as follows: (i) all
elements in $C$ are inserted in $S$; (ii) the depot vertex is inserted $k - 1$ times.

Each permutation of $\mathcal{S}(C, k)$ represents a solution to the VRP. For example, consider the graph and the vertices described in Fig. 2, and suppose that the number of vehicles is three (i.e. $k = 3$). The $\mathcal{S}(C, 3)$ sequence is given by $\mathcal{S}(C, 3) = (c_1, \ldots, c_{13}, \pi, \pi)$. For example, the permutation $\mathcal{S}' = (c_3, c_5, c_4, c_1, \pi, c_6, c_{10}, c_{11}, \pi, c_7, c_8, c_9, c_{13})$ is the solution described in Fig. 2.

All routes begin and end at the depot. The $\mathcal{S}'$ solution represents a partition of the clients in three routes: $\mathcal{R}_1 = (c_3, c_5, c_4, c_1, c_2)$, $\mathcal{R}_2 = (c_6, c_{10}, c_{11}, c_{12})$ and $\mathcal{R}_3 = (c_7, c_8, c_9, c_{13})$. The vertex $\pi$ is used to create a partition of the sequence in $k' \leq k$ routes. Let $\text{Partition}(\mathcal{S}) = (\mathcal{R}_1, \ldots, \mathcal{R}_{k'})$. By definition, empty routes are not part of $\text{Partition}(\mathcal{S})$. Thus, $\text{Partition}(1, 2, \pi, \pi, 3, 4)$ is $\{(1, 2), (3, 4)\}$ and not $\{(1, 2), (3, 4)\}$, i.e. $k' \leq k$.
The length of a route $R = (r_1, \ldots, r_m)$ is given by:

$$W(R) = w(\pi, r_1) + w(r_m, \pi) + \sum_{i=1}^{m-1} w(r_i, r_{i+1}).$$

The length of a solution $S = (s_1, \ldots, s_m)$ is calculated as:

$$W(S) = w(\pi, s_1) + w(s_m, \pi) + \sum_{i=1}^{m-1} w(s_i, s_{i+1}).$$

The sequence $S$ contains edges between deliveries and the depot, other than the first and last edge that need to be included in $W(S)$. The number of vehicles used in a given solution is equal to the number of non-empty routes $|\text{Partition}(S)|$. If the number of vehicles is $k$ and non-empty routes are allowed, we have the constraint $|\text{Partition}(S)| = k$. If the number of vehicles are at most $k$, or if empty routes are allowed, we have $|\text{Partition}(S)| \leq k$. If the number of vehicles is not a part of the input, the domain may be given by the permutation of the $S(C,k)$ sequence. In this case, the number of vehicles is defined during the optimization step.

Given a feasible solution, it is necessary to calculate its costs. The most common objective function to be minimized is the length of the solution:

$$f_1(S) = W(S).$$

Another objective function consists in finding a feasible solution that minimizes the number of vehicles:

$$f_2(S) = |\text{Partition}(S)|.$$  

Suppose there are 25 available mail carriers and a feasible solution with 21 routes. In this case, the post office may allocate the four available mail carriers to other internal tasks.
Finally, it is required that the solution meet the fairness criteria, i.e. routes should be assigned in a way that balances out the workload (route length) among the mail carriers. The way we modeled fairness was through minimizing the variance of the route lengths:

$$f_3(S) = \sqrt{\frac{\sum_{\mathcal{R} \in \text{Partition}(S)} (W(\mathcal{R}) - \bar{W}(\mathcal{R}))^2}{|\text{Partition}(S)| - 1}}.$$ 

VRP is a set of problems that consists of visiting customers using vehicles. Each variant has additional feasibility constraints, such as not allowing empty routes ($|\text{Partition}(S)| = k$). The PostVRP assumes that the length of the route is limited. Let $R_{\text{max}}$ be the maximum allowed route length, i.e. $W(\mathcal{R}) \leq R_{\text{max}}$.

**Definition 1 (PostVRP).** Given a set of elements $S$, a weight function $w : S \times S \rightarrow \mathbb{N}$, a constant $k \in \mathbb{N}$ representing the maximum number of vehicles, a special vertex $\pi \in S$ and a maximum route length $R_{\text{max}} \in \mathbb{N}$. Let $C \leftarrow S \setminus \{\pi\}$. Consider the sequence $S(C, k)$, and let $P_e$ be the set of all feasible permutations of $S(C, k)$ with respect to $R_{\text{max}}$. The PostVRP problem consists of minimizing $(f_1(S), f_2(S), f_3(S))$ subject to $S \in P_e$.

### 4. Model description

This section describes the PostVRP model. We start the process of creating the benchmark by mapping each street onto a street map graph. Each street $St$ is modeled as a polygonal chain, which is defined as a set of planar coordinates. For example, suppose a University St. modeled as a polygonal chain $P = (c_1, \ldots, c_n)$, where $c \in \mathbb{R}^2$ for all $c \in P$. The complete
map graph has a set $\mathcal{P} = (P_1, \ldots, P_n)$ of polygonal chains, one for each street.

We create a graph $G(V, E)$ based on $\mathcal{P}$. Each vertex $v \in V$ is associated with a Cartesian coordinate $(x_v, y_v) \in \mathbb{R}^2$ and each edge $e = (u, v)$ is a straight line segment between $u$ and $v$. The edge weight is $w'(e) = \sqrt{(x_u - x_v)^2 + (y_u - y_v)^2}$. The vertices associated with corners are automatically built by a line segment intersection algorithm.

Fig. 3 (right) displays simple streets modeled as one polygonal chain and streets with islands, which are modeled by two parallel polygonal chains. Additional segments are added to allow shortcuts in footpaths.

![Fig. 3. A section of the city map (left). Edges and vertices created over the city map (right).](image)

Given an edge $e$, its street is denoted by $St(e)$. Each street $St$ has an arbitrarily defined width $wth(St) \in \mathbb{R}^+$ that represents the cost of crossing the street. The value $wth(St)$ can be set to zero, thus resulting in no cost to cross the street.

A non-normalized probability density $D(St)$ is assigned to each street. The probability of a street receiving a delivery workload per unit length is directly proportional to the density value $D$. Such value is used to create a central street with a large workload compared to a distant one. The probabilities are outlined in the next subsection.
4.1. Generating delivery points

Consider a street map graph $G(V, E)$. The probability of one delivery being assigned to an edge $e$, denoted by $\text{Prob}(e)$, is:

$$\text{Prob}(e) = \frac{D(\text{St}(e))w'(e)}{T},$$

where $T = \sum_{e'} D(\text{St}(e'))w'(e')$. $\text{Prob}(e)$ is directly proportional to the edge length $w'(e)$ and to the probability density $D(\text{St}(e))$, and it must be normalized to obtain $\sum_{e \in E} \text{Prob}(e) = 1$.

The location of a given delivery $d$, denoted by $\text{loc}(d)$, is composed of three attributes: an edge $(u, v)$, a value $\alpha \in [0, 1]$ and a label $\text{street}_\text{side} = \{\oplus, \ominus\}$. The delivery is positioned at the affine combination of $u$ and $v$ in respect to $\alpha$, i.e. $(x_u, y_u)(\alpha) + (1 - \alpha)(x_v, y_v)$. The street of a delivery $d = (e, \alpha, s)$, denoted by $\text{St}(d)$, is the street of the edge $\text{St}(e)$.

An integer $n$ represents the number of deliveries, and an artificial delivery $d_\pi$ is created for the depot. The value of $\alpha$ is randomly generated within the interval $[0, 1]$. The street side label is an equiprobable random choice in the set $\{\oplus, \ominus\}$. Algorithm 1 is then used to create the delivery set. Given that the number of deliveries is a part of the input, it is possible to set arbitrarily large instances.

4.2. Defining the weight between a pair of deliveries

The street map graph $G(V, E)$ is used to compute the weight between deliveries. Given two deliveries $d_a$ and $d_b$, the cost to cross the street is defined as:

$$\text{cross}(d_a, d_b) = \begin{cases} 
\text{wth}(\text{St}(d_a)), & \text{if } (d_a, d_b) \text{ side labels are } \{(\oplus, \ominus), (\ominus, \oplus)\} \\
0, & \text{otherwise.}
\end{cases}$$
Input: An integer $n$ and a set of edges $E$ with probabilities $\text{Prob}(e)$, $\forall e \in E$

Output: A set of deliveries $\text{Del}$.

1. $\text{Del} \leftarrow \emptyset$
2. Partition all edge probabilities in the interval $[0, 1]$
3. for $i = 1$ to $n$ do
   4. Select a random value $r \in [0, 1]$
   5. if $r$ is in the interval associated with $\text{Prob}(e)$ then
   6. Select a random value $\alpha \in [0, 1]$
   7. Select a random street side value $s \in \{\oplus, \ominus\}$
   8. $\text{Del} \leftarrow \text{Del} \cup \{(e, \alpha, s)\}$
5. end
6. return $\text{Del}$

Algorithm 1: Algorithm to create deliveries.

A constant $\beta \in \mathbb{R}^+$, that represents an additional fixed cost per delivery, must be defined. The weight between two deliveries $d_a = (e_a, \alpha_a, s_a)$ and $d_b = (e_b, \alpha_b, s_b)$ is given by $w(d_a, d_b)$. If $e_a = e_b$ then:

$$w(d_a, d_b) = |\alpha_a - \alpha_b|w'(e_a) + \text{cross}(d_a, d_b) + \beta.$$ 

Let $G(V, E)$ be the original street map, $e_a = \{u_a, v_a\}$, $e_b = \{u_b, v_b\}$, and let $G^*(V^*, E^*)$ be defined as: $V^* = V \cup \{d_a, d_b\}$, $E^* = E \cup \{(u_a, d_a), (v_a, d_a), (u_b, d_b), (v_b, d_b)\}$ (Fig. 4), thus:

$$w(d_a, d_b) = \text{minpath}(d_a, d_b, G^*) + \text{cross}(d_a, d_b) + \beta.$$ 

The instance is composed of a matrix $w_{n \times n}$, an integer $k$, and an integer $\mathcal{R}_\text{max}$. The first delivery represents the depot.

4.3. The benchmark tool

This subsection describes the tool that creates the benchmark. It has three configuration files, background.png, model.txt and instances.txt. The background file contains an image used to improve visualization and its resolution is used as the base for the model. The model file must contain the following information:
Fig. 4. The cost between two deliveries $d_a$ and $d_b$ located at distinct edges $e_a$ and $e_b$, respectively.

- Depot location: the coordinate position reference to the depot;
- Additional cost per delivery: cost to hand out the delivery;
- Decimal precision: number of digits after the fractional part;
- Pixel value: value used to convert a pixel into other units;
- Attributes: attributes used to compute the street probability density and the cost to cross the street;
- Roadmap: the description of streets including the polygonal chain.

Consider a white background with $500 \times 500$ pixels and the model described in Fig. 5. The tool will process the model file and create a roadmap (Fig. 6). The depot is positioned at the closest edge. The probability density $D$ of the 4th Av is 0.4 because it is a $[AVE,PERIPHERAL,RADIOACTIVE]$ with values $\{20, 0.2, 0.1\}$.

Fig. 5. Example of a model file.

The last file is named $instance.txt$ (Table 1). Each line corresponds to an instance in the benchmark. It must contain the instance ID, the directory
Table 1. Instance file.

| ID | Dir  | Subdir | n  | k  | $R_{\text{max}}$ | Comment          | Seed  | MD5    |
|----|------|--------|----|----|----------------|-----------------|-------|--------|
| 0  | ex   | ex_0_0 | 0  | 0  | 2941.15       | Max route [...]  | 100   | 4d...af|
| 1  | ex   | ex_10_5| 10 | 5  | 2941.15       | The size [...]   | 101   | e9...10|
| 2  | ex   | ex_100_5| 100| 5  | 2941.15       | Consider [...]   | 102   | eb...a2|
| 3  | ex   | ex_1000_5| 1000| 5  | 2941.15      | Instance [...]   | 103   | 05...62|
| 4  | ex   | ex_10000_5| 10000| 5  | 2941.15     | Instance [...]   | 104   | 93...53|

The MD5 checksum value is used to ensure the instance identity. The tool will recreate the instances offline and verify the MD5 signature in the instance file. The tool will execute the files of Fig. 5 and Table 1 and create the instances shown in Fig. 7.

One can edit the instance file to create new instances for a given model. Once the new instances are created, it is necessary to manually update the MD5 signature. For instance, a new seed will create a new instance with
another pseudo random sequence.

The project site (Meira et al., 2017) provides the source program that parses the instance file. The program executes a simple swap optimization and saves the route in both a text file and an image file (Fig. 8). The purpose is to provide the researcher with a parse to the instance file and a visualization of the solution.

5. Real-world PostVRP benchmark (RWPostVRPB)

In this section, the tool is used to model a real-world mail delivery in the city of Artur Nogueira, Brazil, namely RWPostVRP. To make the instances as realistic as possible, the authors relied upon domain expertise from an actual post office in the aforementioned city.

We build the model from a hard copy image instead of using existing street map graphs for the following reasons: (i) the path on foot may differ
from the ones available from graphs which prioritize delivery by vehicles; 
(ii) the number of streets in Artur Nogueira is sufficiently small to allow 
the manual creation of the graph (≈ 400 streets); and (iii) currently, public 
maps such as OpenStreetMap (Haklay & Weber, 2008) are incomplete, i.e., 
the city has a large number of streets not covered so far.

The tool automatically computes corners resulting in a graph with $|V| = 2111$ and $|E| = 3225$. Each vertex is associated with a pixel and each edge 
is associated with a straight line between the two edge pixels. The cost of 
an edge $(u, v)$ is directly proportional to the Euclidean distance between 
vertices $u$ and $v$ in $\mathbb{R}^2$.

Each street is classified using the Region (R), Type (T) and Zone (Z) 
attributes. Each attribute has a corresponding number of levels and each 
attribute-level pair is associated with a multiplicative penalty (Pen) in $\mathbb{R}^+$. 
Table 2 contains the assignment of attribute, level and penalty based on 
expert knowledge.

In the proposed model, streets located in the downtown area have a 
higher delivery rate per unit length than the ones located in the outskirts.
Such behavior is captured by the Region attribute through four levels: central, peripheral, distant and isolated. The Type attribute has also four levels, namely avenue, street, way and highway, while the Zone attribute may be commercial, mixed, and residential. We used Google Maps as an auxiliary tool to classify streets. Each one of the 422 streets received a value in \( R \times T \times Z \), according to expert knowledge.

The (non-normalized) probability density \( D : Streets \rightarrow \mathbb{R}^+ \) is obtained from the multiplicative penalties. For example, the 15\(^{th} \) Avenue is (central, avenue, mixed), thus \( D(15^{th}) = 1 \times 1 \times 0.7 = 0.7 \). On the other hand, Jasmine street is (isolated, way, residential), thus \( D(Jasmine) = 0.2 \times 0.2 \times 0.4 = 0.16 \). In this example, a random delivery to the 15\(^{th} \) avenue is \( \frac{0.7}{0.16} \) more probable than a delivery to Jasmine way by unit length.

The RWPostVRPB contains 78 instances divided in four groups, Toy, Normal, OnStrike, and Christmas (Table 3). The Toy set contains 30 instances with a small number of deliveries, and it may be used to validate algorithms before their use with realistic and larger instances.

### Table 2. Attribute, level and penalty values.

| Attribute | Level 1\(_{\text{Pen}}\) | Level 2\(_{\text{Pen}}\) | Level 3\(_{\text{Pen}}\) | Level 4\(_{\text{Pen}}\) |
|-----------|-----------------|-----------------|-----------------|-----------------|
| Region(R) | central\(_{(1,0)}\) | peripher\(_{(0.75)}\) | distant\(_{(0.4)}\) | isolated\(_{(0.2)}\) |
| Type(T)   | avenue\(_{(1,0)}\) | street\(_{(0.75)}\) | way\(_{(0.4)}\) | highway\(_{(0)}\) |
| Zone(Z)   | commercial\(_{(1,0)}\) | mixed\(_{(0.75)}\) | residential\(_{(0.4)}\) | — |

### Table 3. RWPostVRPB instances description.

| Set       | # Instances | # Deliveries | Length (hrs) | # Vehicles (max) |
|-----------|-------------|--------------|--------------|------------------|
| Toy       | 30          | 3 to 5,000   | 6            | 5 to 15          |
| Normal    | 15          | 10,000 to 14,000 | 6       | 30               |
| OnStrike  | 15          | 15,000 to 19,000 | 8       | 30               |
| Christmas | 18          | 20,000 to 30,000 | 8       | 30               |
The Normal set contains 15 instances from 10,000 to 14,000 deliveries. Artur Nogueira city has around 50,000 inhabitants and an average of 12,000 daily mail deliveries. The normal daily work of a mail carrier has eight hours a day. The mail carrier spends two hours preparing the deliveries inside the post office and six hours to complete the deliveries on foot. The post office has around 15 mail carriers to perform the deliveries. The number of vehicles is variable in PostVRP, with a maximum value of 30 in Normal set instances. If a feasible solution with 11 mail carriers is found, the post office may assign four mail carriers (15 – 11) to internal tasks.

The OnStrike and Christmas sets may be used to model contingencies. The OnStrike set is similar to Normal, but the number of deliveries is larger (from 15,000 to 19,000) and the maximum route length is eight hours. The Christmas set models special seasons with high delivery rates. The post office often hires extra mail carriers for the Christmas season. A feasible solution with 17 mail carriers represents two new hires (15+2). For all sets, a minimum average route length is desired as well as a minimum variance between the lengths of the routes. Fig. 9 shows the distribution of 10,000 delivery points for a chosen area of Artur Nogueira.

The full set of instances can be downloaded from the project website (Meira et al., 2017). The website also includes a pilot sample modeling a section of Manhattan NY.

6. Conclusion

In this paper, we introduced the PostVRP, a multi-objective VRP variant with a route length constraint. The three objectives to be minimized were: (i) the number of vehicles, (ii) the average length and (iii) the stan-
Fig. 9. Part of an instance generated with 10,000 delivery points.

dard deviation of the length of the routes.

A feasible solution that reduces the number of mail carriers increases the revenues, since such mail carriers can be allocated to other tasks. A solution that reduces the route length also reduces delivery effort, which translates to increased profit as well. Reducing the standard deviation is also desirable for the sake of fairness of the solution.

By using the tool, we created a benchmark that models a problem that comprised the mail delivery on foot in a Brazilian city. The instances were classified into four groups: (i) Toy, with up to 5,000 deliveries, (ii) Normal, with up to 14,000 deliveries, (iii) OnStrike, with up to 19,000 deliveries, and (iv) Christmas, with up to 30,000 instances.

The application of the tool allows the generation of arbitrary and large
instances in the proposed benchmark by changing the number of deliveries in the instance file. Likewise, new instances can be created by changing the seed of the instance. Additionally, researchers may also model new scenarios. To our knowledge, this is the first VRP benchmark with up to 30,000 delivery points that models a real-world scenario.

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