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ARTICLES

NEW MULTI-OBJECTIVE VRP INSTANCES MODELLING MAIL DELIVERIES FOR RIO CLARO CITY, SÃO PAULO, BRAZIL

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ABSTRACT. Optimization benchmarks are tools for the validation and comparison of algorithms. Routing benchmarks are particularly relevant to industry. However, there are few available VRP benchmarks based on realistic situations. This research creates a set of multi-objective (three objectives) instances for a length-constrained variant of VRP. The instances model a realistic case of mail delivery performed by mail carriers on foot in the Brazilian city of Rio Claro. A new graph of the city road map was created, and mail carriers' activities were estimated. Streets were assigned with distinct probability densities to receive deliveries. This research produces 80 mail delivery instances with up to 50,000 deliveries per instance. Finally, bounds for a set of instances were produced. The instances are publicly available for the community to test, compare and validate multi-objective optimization algorithms.

Keywords: VRP instances, multi-objective, logistics.

1 INTRODUCTION

Logistics is present in several activities of modern daily life and is a field of scientific study. Logistical optimization can reduce costs for many economic activities. Computer science brings solutions to real-world decision-making problems.

One of the computational problems involving logistics is the Traveling Salesman Problem (TSP). A generalization of the TSP is the Vehicle Routing Problem (VRP). The VRP was introduced by Dantzig & Ramser (1959). It was initially defined as a problem of fueling multiple trucks for a single refinery. However, the name VRP only appears in the paper of Christofides (1976), where VRP was defined as a generic class of problems involving the visit of "customers" by "vehicles".

Since then, several variants of the VRP have emerged, modeling different situations, bringing different characteristics and requirements. The most studied variant assumes a capacity in vehicles,

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which can be a maximum weight or volume supportable by a vehicle. Such restriction implies a maximum number of deliveries that a given vehicle can perform. Capacity can be variable or equal for vehicles. This variant is named Capacitated Vehicle Routing Problem (CVRP).

Assuming time windows, in which deliveries have a specific time window to be performed, we have the Vehicle Routing Problem with Time Windows (VRPTW).

There is also the possibility of using several depots. Such problems are called Multi Depot Vehicle Routing Problem, (MDVRP). According to Eksioglu et al. (2009), about 11% of the papers assume the variant with multiple deposits, 90.5% for CVRP and 37.9% for VRPTW.

According to Talbi (2009), scientists, engineers and managers always make decisions. As the world becomes more and more complex, the decision process must be made in a rational and optimized way.

For Talbi (2009), the decision process consists of four steps: *(i)* formulate the problem; *(ii)* model it; *(iii)* optimize it; and *(iv)* implement a solution.

In the first step, the problem is identified, and an initial formulation is made. This formulation may be inaccurate. Internal factors, external factors and goals are outlined.

In the second stage, a mathematical model is built for the problem, which can be inspired by similar models found in the literature. In these cases, the problem is reduced to better studied models. Generally, every model is a simplification of reality, being usually incomplete. Modeling may present approximations and some phenomena may not be represented because they are too complex or not very relevant for the intended objectives.

Once the problem is modeled, a good solution must be generated for it, which can be optimal or sub-optimal. Next, the decision process can be implemented, and the proposed solution can be tested. However, benchmarks allow the performance of processes to be tested before someone implements a solution in the real world.

Benchmarks are commonly found tools in computing and other areas, and they allow us to evaluate the performance of products and methods. Benchmarks model a problem, allow the performance evaluation of algorithms and solutions. There are several benchmarks known in the literature. The best known to TSP is the TSPLIB (Reinelt, 1991). The TSPLIB brings a group of several instances of different papers, being available in Reinelt (1995). Although the TSPLIB has instances for the symmetric and asymmetric TSP, it also has instances of related problems, such as the CVRP, the sequential ordering problem, and the Hamiltonian Cycle.

Vidal et al. (2020) creates a concise guide about VRP variants using three main subdivisions: *(i)* Metrics, objective functions and the combination of objective functions. *(ii)* Routing optimization integrated with business decision-making. *(*iii) Model precision improvement.

In this direction, in Meira et al. (2020) there is the construction of a benchmark for the VRP. That research analyzes the problem of mail delivery by mail carriers in the city of Artur Nogueira, Brazil. The variant is called PostVRP.

PostVRP considers vehicles with no capacity, a maximum route limited and only one depot. That research develops a methodology for probabilistic deliveries generation in a roadmap space and a method for calculating distances by the shortest path algorithm. The instances generated in Meira et al. (2020) contain up to 30,000 deliveries. In PostVRP there is a multi-objective approach, since it considers three objectives: *(i)* the minimization of the total route length; *(ii)* the minimization of the number of vehicles and (*iii*) the reduction of the variability in the length of the routes.

The focus of this research is to create multi-objective instances for mail deliveries on foot in the city of Rio Claro, State of São Paulo (SP), Brazil, located at 22° 24' 39" S, and 47° 33' 39" W. The mathematical model was created based on the expert knowledge of one author, who lives in Rio Claro. This research generates new instances for the variant PostVRP with up to 50,000 deliveries and up to 120 vehicles. We named the new instances as RioClaroPost.

The roadmap generated in this research presents 1,674 streets. We preliminary present results using the 2-opt algorithm (Croes, 1958) to validate the new instances.

2 LITERATURE REVIEW

Let n be the VRP number of clients. The first known instance of VRP was proposed in the paper of Dantzig & Ramser (1959), who introduced the problem. Such work contains only one instance, with $n = 12$, for the CVRP variant. The research introduced the algorithm that was later improved by Clarke & Wright (1964), known as the savings heuristic.

Solomon's paper (1987) extends the savings heuristic to the VRPTW. This paper also brings a new set of 56 instances, all with $n = 100$ divided into six problem sets: $R1$ and $R2$ being randomly generated through a uniform distribution, $C1$ and $C2$, which were generated through clustering, $RC1$ and $RC2$, which contain a mix between clustered and randomly generated data. Each set has from eight to 12 instances. The instances of sets $R1$, $C1$, $RC1$ have more restricted route times compared with sets $R2$, $C2$ and $RC2$. According to Solomon, several factors can affect the behavior of routing and scheduling heuristics, such as: geographic data, the number of customers served by a vehicle, and features such as time constraints. Gehring & Homberger (1999), extended Solomon's instances to create a new benchmark.

The authors of this research created six groups of instances, in which the first group contains the 56 original instances of Solomon (with $n = 100$) and the other five groups containing 60 instances with $n = 200$, $n = 400$, $n = 600$ and $n = 1,000$. The research kept the same six classes defined by Solomon: $R1$, $R2$, $C1$, $C2$, $RC1$ and $RC2$. Each class contains ten instances.

In 2012, Ma et al. (2012) created 56 instances based on Solomon. They modeled a new problem, which was named VRP with Time Windows and Link Capacity Constraints (VRPTWLC). This variant added a new restriction to VRPTW. Such restriction consists of the insertion of maximum capacity to streets and accesses. Such streets and accesses are forbidden for some vehicles. The instances generated by this research are practically the same as Solomon's, with street capacity added.

Uchoa et al. (2017) created two sets of instances for CVRP. The main set contains 100 new instances containing n between 100 and 1,000 clients. The extended set has 600 new instances. The focus of the research was to generate less artificial and less homogeneous instances, avoiding patterns that are unlikely to appear in real data.

Lee & Chae (2021) proposed a new set of 648 instances with n between 50 and 500 for the Asymmetric Costs VRP (ACVRP). This benchmark models Seoul and Busan instances in South Korea, using the SK Telecom API.

Elgharably et al. (2022) introduced a multi-objective model for the Green Vehicle Routing Problem (GVRP) based on the instances of Uchoa et al. (2017). The authors considered three objectives: *(i)* to minimize the total operational cost; *(ii)* to minimize the environmental impact; and *(iii)* to maximize customer satisfaction. The problem addressed by this work is also considered stochastic because of its uncertainties. Three models are proposed by this work: the first considers uncertainty in travel time, whereas the other models address uncertainties about demands.

Gunawan et al. (2021) provided a list of instances of different works. The primary reference is the research of Mendoza et al. Mendoza et al. (2014), which made available variants of VRP on an open platform called VRP-REP. The VRP-REP defined 48 VRP variants divided in 100 sets, resulting in 8,683 instances.

3 PROBLEM DEFINITION

This section was based on research (Meira et al., 2020), where the authors defined the problem as a variant of the VRP based on the delivery of mail by mail carriers in the Brazilian city of Artur Nogueira, through a benchmark with instances of up to 30,000 vertices. The research presents only one depot and a maximum route length R_{max} allowed for the solution.

The authors in Meira et al. (2020) considered a complete weighted graph $G(V,E,w)$ and a cost function $w: E \to Q^+$. There is a special vertex $\pi \in V$ called deposit. The set of clients is given by $C = V \setminus \{\pi\}$ and their number by $n = |C|$. The set of clients is represented by $C = \{c_1, \ldots, c_n\}$. There is a value $k \in \mathbb{N}$ that represents the number of vehicles, which can be a constant or a variable.

Consider a sequence $S(C,k) = (c_1, \ldots, c_n, \pi, \ldots, \pi)$ assembled by inserting all the elements of C into $S(C,k)$. After that, the vertex of the deposit is inserted $k-1$ times. Each permutation of $S(C,k)$ represents a VRP solution.

All routes start and end at the depot. Each route is a subsequence of S limited by π. For example, consider the solution $S' = (c_1, c_2, c_3, c_4, \pi, c_5, c_6, c_7, \pi, c_8, c_9, c_{10})$. In this example, $R_1 = (c_1, c_2, c_3, c_4)$, $R_2 = (c_5, c_6, c_7)$ and $R_3 = (c_8, c_9, c_{10})$. Let $Partition(S) = (R_1, \ldots, R_{k'})$ be the set generated by breaking the original sequence into routes. The break occurs every time the deposit is found in the original sequence. By definition, empty routes are not part of $Partition(S)$. That is, $Partition(1,2,\pi,\pi,3,4)$ is $\{(1,2),(3,4)\}$ and not $\{(1,2),(),(3,4)\}$.

The size of the 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 average length of a solution $S = (s_1, \ldots, s_m)$ is calculated as the average length of the routes, as follows:

$$W(S) = \frac{\sum\limits_{R \in Partition(S)} W(R)}{|Partition(S)|}$$

The number of vehicles used in a given solution is equal to the number of non-empty routes, i.e. $|Partition(S)|$. If the number of vehicles is k and empty routes are not allowed, we have the restriction $|Partition(S)| = k$. If the number of vehicles is k at most, or if empty routes are allowed, we have $|Partition(S)| \leq k$.

Similarly to Meira et al. (2020), we defined three optimization objectives: $f_1(S)$, $f_2(S)$ and $f_3(S)$. The $f_1(S)$ is $W(S)$. The function $f_2(S) = |Partition(S)|$ that represents the number of vehicles. Finally, the function $f_3(S)$ measures the degree of variability between the lengths of the routes by calculating the standard deviation:

$$f_3(S) = \sqrt{\frac{\sum\limits_{R \in Partition(S)} (W(R) - \overline{W(R)})^2}{|Partition(S)| - 1}}$$

The mail carrier has a limit of six or eight hours of work per day. As the value $W(R)$ is measured in time, the solution must respect $W(R) \leq R_{max}$ for a given $R_{max} \in \mathbb{N}$. The formal definition of the problem is presented below:

Definition 1. ***PostVRP***.

Given a set of elements S, a cost function $w : S \times S \to \mathbb{N}$, a constant $k \in S$ represents the maximum number of vehicles, a special vertex $\pi \in S$ is the depot, the $R_{max} \in \mathbb{N}$ is the maximum length of the route. Considering $C \leftarrow S \setminus \{\pi\}$, the sequence $S(C, k)$ and Pe is the set of all feasible permutations of $S(C, k)$ respecting the R_{max}. PostVRP consists of the minimization of $(f_1(S'), f_2(S'), f_3(S'))$ for every $S' \in Pe$.

4 METHODOLOGY

As in Meira et al. (2020), streets are modeled as a polygonal chain P defined as a set of planar coordinates, such that $P = (c_1, \ldots, c_n)$, where $c \in \mathbb{R}^2$ for all $c \in P$. The graph $G(V, E)$ is generated from the set of these streets. Each vertex $v \in V$ is associated with a Cartesian coordinate $(x, y) \in \mathbb{R}^2$ and each edge $e = (u, v)$ is a line segment between u and v. Edge cost is defined by Euclidean distance. See Figure 1.

We use a probability density to assign probabilities of streets receiving deliveries as in Meira et al. (2020). This method is used because central streets are more likely to receive deliveries compared to isolated streets per unit of length, simulating the population density of a real urban area.

The research (Meira et al., 2020) presents a tool for creating benchmarks. We use this tool to create a set of instances to the city of Rio Claro. This tool has three configuration files to be defined:

- *Background.png*: contains an image used for viewing. This image also serves as the basis for building the model.
- *Model.txt*: contains information about the model, such as: additional cost to perform a delivery, vehicle speeds, density street attributes, depot location and the street map.
- *Instances.txt*: contains the attributes of each instance, such as maximum number of vehicles, number of deliveries and maximum size of each route.

We started the construction of the instances by manually extracting the coordinates corresponding to the streets from the Rio Claro's map. At this stage, 1,674 streets were extracted. Figure 1 illustrates the extraction of streets and the representation of some streets modeled through this process. Corners are computed automatically by the tool.

The construction of the model was based on a cropping of a digital image of the map of Rio Claro available on the city's website. Similarly to the research of Meira et al. (2020) each street was classified using the attributes Region (R), Type (T) and Zone (Z). The classification of streets was based on the knowledge of one of the authors, who lives in the region. The assigned probabilities, penalties and nomenclatures in use also follow the pattern defined by Meira et al. (2020) as shown in Table 1.

Table 1 – Street Attributes. Penalty attribute, level and values. A 0.4 value means that the density of deliveries is multiplied by the value 0.4. Source: Meira et al. (2020).

Attribute	Level 1$_{(pen)}$	Level 2$_{(pen)}$	Level 3$_{(pen)}$	Level 4$_{(pen)}$
Region(R)	central$_{(1.0)}$	peripheral$_{(0.75)}$	distant$_{(0.4)}$	isolated$_{(0.2)}$
Type(T)	avenue$_{(1.0)}$	street$_{(0.75)}$	path$_{(0.4)}$	highway$_{(0)}$
Zone(Z)	commercial$_{(1.0)}$	mixed$_{(0.75)}$	residential$_{(0.4)}$	-

Each street in Rio Claro received an attribute Region, among the values *central* (penalty 1), *peripheral* (penalty 0.75), *distant* (penalty 0.4) and *isolated* (penalty) 0.2. Penalty 0.4 means that the density of deliveries is multiplied by the value 0.4.

Each street in Rio Claro received an attribute *type*, with values *avenue*, *street*, *path* and *highway*, with penalties $(1; 0.75; 0.4; 0)$, respectively.

Finally, each street in Rio Claro received an attribute *zone* with values *commercial*, *mixed* and *residential* with penalties $(1; 0.75; 0.4)$, respectively.

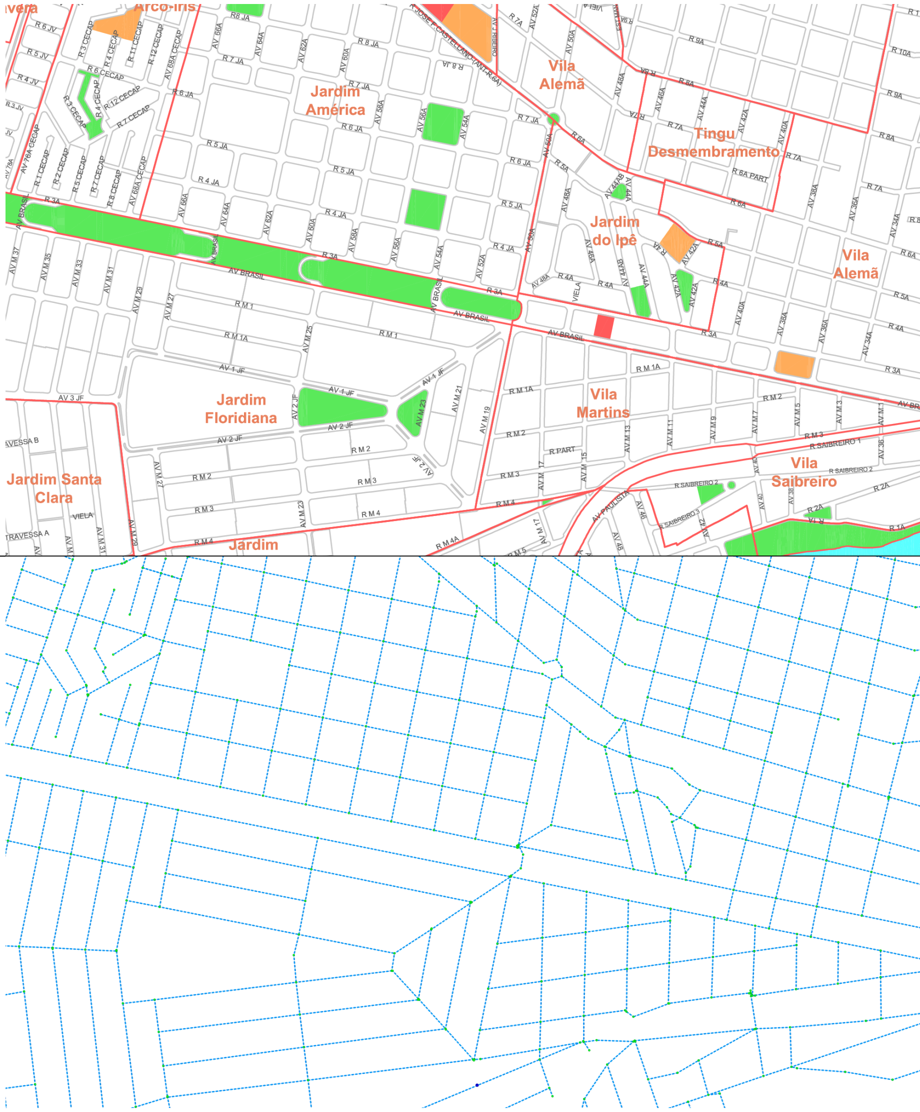

Figure 1 – Street modeling. Above a cropping of the original map and below the extracted streets (dashed in blue). The streets were extracted manually as a polygonal chain.

The authors in Meira et al. (2020) created a graph $G(V,E)$. 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 $w'(e) = \sqrt{(x_u - x_v)^2 + (y_u - y_v)^2}$. An edge e is associated with its street $St(e)$.

The authors in Meira et al. (2020) assigned a non-normalized probability density $D(St)$ to each street St. Such density is the product of the streets's penalties. The probability of a street receiving a delivery workload per unit length is directly proportional to the density value D. Such a value is used to create a central street with a large workload compared to a distant one.

The paper uses a probability of one delivery being assigned to an edge e, denoted by $Prob(e)$:

$$Prob(e) = \frac{D(St(e))w'(e)}{T}, \text{where } T = \sum_{e' \in E} D(St(e'))w'(e').$$

$Prob(e)$ is directly proportional to the edge length $w'(e)$ and to the probability density $D(St(e))$, and it must be normalized to obtain $\sum_{e \in E} Prob(e) = 1$. The location of a given delivery d, denoted by $loc(d)$, is composed of three attributes: an edge (u, v), a value $\alpha \in [0, 1]$, and a label $street\_side \in \{\oplus, \ominus\}$. The delivery is positioned at the affine combination of u and v in respect to α, that is, $(x_u, y_u)(\alpha) + (1 - \alpha)(x_v, y_v)$. The street of a delivery $d = (e, \alpha, street\_side)$, denoted by $St(d)$, is the street of the edge $St(e)$. The value of α is randomly generated within the interval $[0, 1]$. The street side label is an equiprobable random choice in the set $\{\oplus, \ominus\}$.

In Meira et al. (2020), the algorithm partitioned all edge probabilities in the interval $[0, 1]$. For each delivery, select a random value $r \in [0, 1]$. If r is in the interval associated with $Prob(e)$, create a delivery $d = (e, \alpha, s)$, where s is a random choice in $\{\oplus, \ominus\}$.

5 RESULTS

The Rio Claro Post contains 80 instances starting with three delivery points and ending with 50,000 delivery points. Figure 2 presents a complete image of the model. Figure 3 shows a cropping of the central region for an instance with 30,000 delivery points. Each delivery point is probabilistic generated. Figure 4 shows the complete map only with the modeled streets represented by the dashed lines in blue. Each street is a polygonal chain. Corners are automatically calculated.

Vehicle speed ($PIXEL\_VALUE$) was defined in the *model.txt* file as 0.886 s/pixel, equivalent to approximately 4.6 km/h, which represents the walking speed of a mail carrier. This constant serves to establish a direct relation of a pixel to seconds. The additional cost per delivery was set at four pixels, equivalent to three seconds per delivery. This means that a delivery consumes an additional time to be performed, not related to distance or speed. The maximum allowed route was 32,505 pixels in some instances and 24,379 pixels in others, representing a daily workload of eight or six hours, respectively.

The instances were established following the pattern of groups defined by Meira et al. (2020), with instances *Toy, Normal, OnStrike* and *Christmas* as in Table 2. *Toy* instances have a small number of deliveries compared to a realistic problem. *Normal* instances contain a more realistic number of deliveries. The maximum length in *OnStrike* instances grows up to eight hours. Finally, *Christmas* instances contain a large number of deliveries, making it more difficult to use any strategy.

Once the three files are filled, the benchmark tool executes and creates the 80 instances. Each instance file contains the matrix w_{ij} with the cost measured according to the time required to

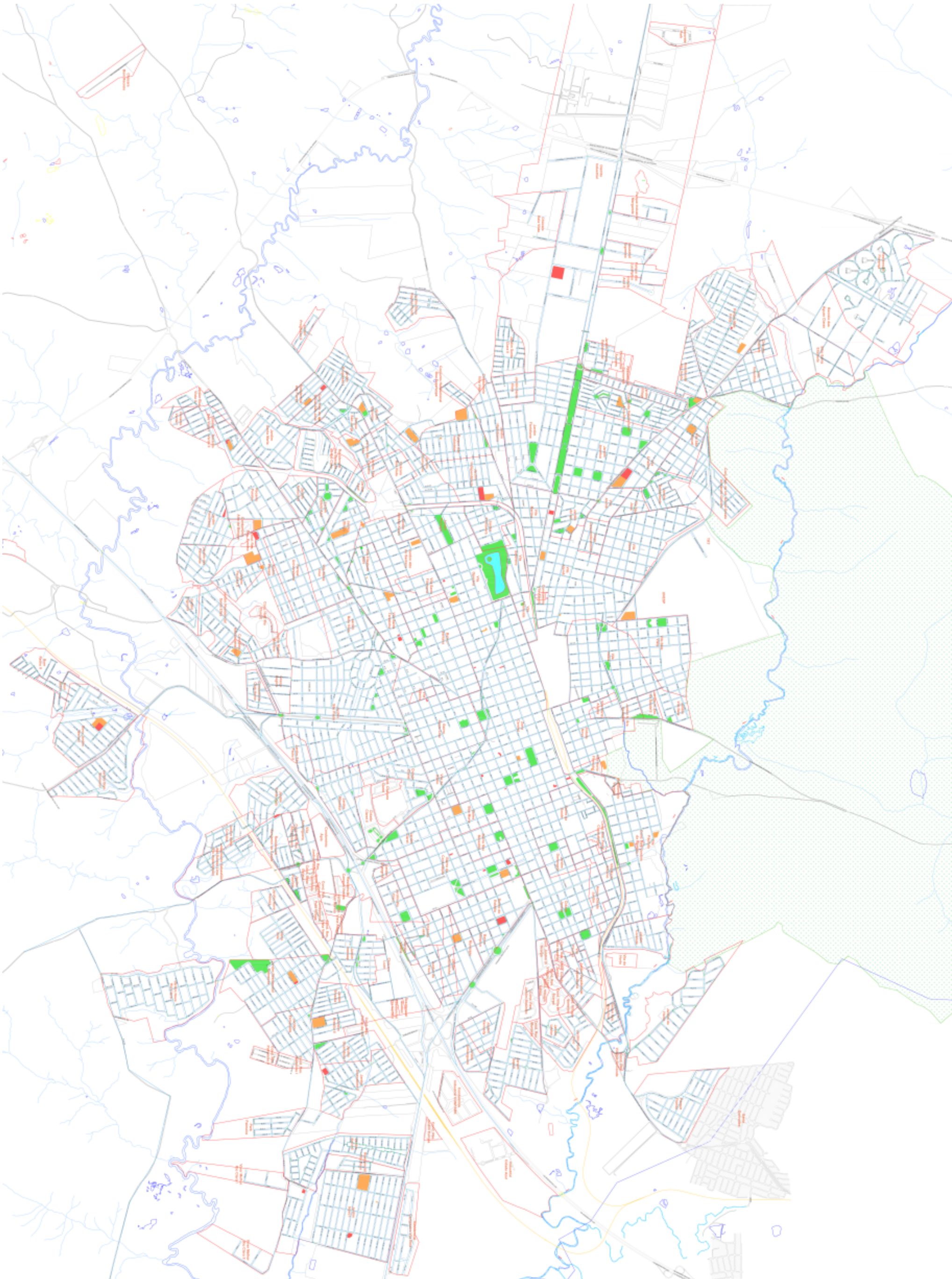

Figure 2 – Complete map of the city of Rio Claro. The map was the base for the manual extraction of the streets and used as a background image for the instances. Source: Rio Claro City Hall website.

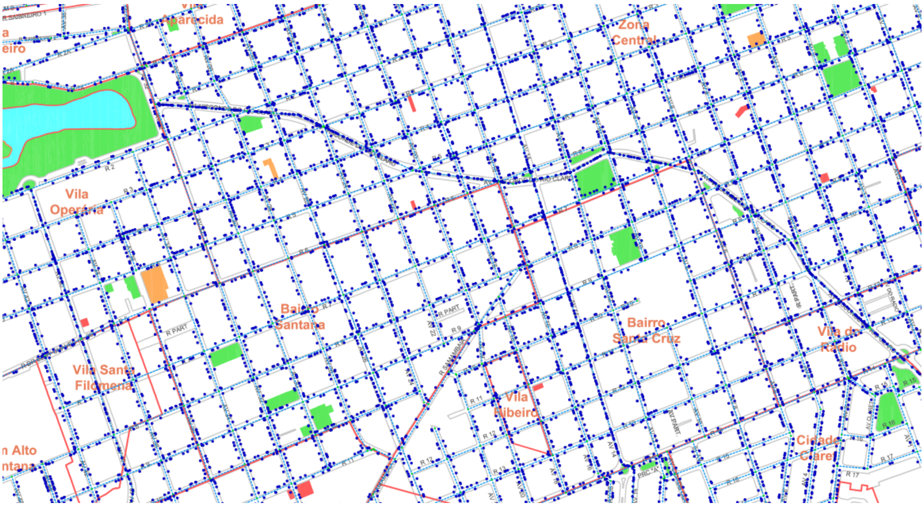

Figure 3 – RioClaroPost instance 75 with 30,000 delivery points. Cropping of the central region. Each blue dot corresponds to a probabilistically generated delivery.

Table 2 – RioClaroPost instance groups.The instance groups were established following the pattern of groups defined by Meira et al. (2020).

Group	#Instances	#Deliveries	Max Len.(h)	#Vehicles(max)
Toy	30	3 to 5,000	6	3 to 45
Normal	15	10,000 to 14,000	6	90
OnStrike	15	15,000 to 19,000	8	90
Christmas	20	20,000 to 50,000	8	90 to 120

make delivery j starting from delivery i. The instance file contains additional information as maximum route length, position of each delivery, maximum number of vehicles and more. The 80 instances use 195GB of memory in plain text format.

5.1 Instances Validation

We obtained an initial result for the instances of RioClaroPost by using the 2-opt algorithm. The algorithm was executed five times for each instance.

At first, we optimized a single route containing all deliveries, similarly to the TSP problem. Then, the route was split by using a greedy route-first, cluster second algorithm. Table 3 contains results obtained for some instances.

We used the index W/R_{max}, which is obtainable by dividing the total length of the single route by the value of R_{max}. This value represents the number of mail carriers needed to cover the TSP cycle in sequence, without returning to the depot at each vehicle change. If the TSP cycle is

Figure 4 – Streets of the Model (blue). The streets were obtained by manual extraction over the city map (Figure 2).

optimum, W/R_{max} is a lower bound to the number of vehicles. In our case, the non-optimum solution produces a W/R_{max}, which is just a reference index.

The results about the vehicles were obtained through the division of routes by the greedy algorithm. Figure 5 contains Table 3 data. It compares the number of instance deliveries with *(i)* the

Table 3 – RioClaroPost results of 2-opt algorithm followed by a route-first cluster second algorithm. The results were obtained through five executions for each instance.

ID	#Deliveries	W/R_max avg±std	#vehicles avg±std	time(s) avg±std
12	50	1.78±0.03	2.8±0.4	0.001±0.002
15	100	2.72±0.04	4.0±0.0	0.0±0.0
18	200	4.10±0.06	6.2±0.4	0.004±0.003
21	500	6.36±0.06	9.0±0.0	0.022±0.002
24	1000	8.91±0.05	13.0±0.0	0.14±0.01
27	5000	18.15±0.07	26.0±0.0	3.6±0.1
30	10000	24.75±0.08	35.4±0.5	18±3
45	15000	22.09±0.08	28.6±0.5	42±2
51	17000	23.15±0.06	29.8±0.4	65±4
60	20000	24.79±0.10	32.2±0.4	120±13
63	22000	25.66±0.03	33.0±0.0	174±14
66	24000	26.69±0.10	34.2±0.4	209±9
69	26000	27.73±0.08	35.8±0.4	281±19
72	28000	28.28±0.04	36.4±0.5	348±19
75	30000	29.32±0.07	38.0±0.0	445±32

number of vehicles obtained after the greedy algorithm and *(ii)* the W/R_{max} index. It should be observed that the value of W/R_{max} and the number of vehicles after the division fits an amortized delivery cost. The larger the number of deliveries, the cheaper the cost of each delivery. The first derivative represents the number of vehicles by delivery, and it is decreasing.

There is a break in the continuity of the curves. It happens where the maximum length grows from six to eight hours by vehicle. It occurs between the *Normal* and *OnStrike* instances.

The time to execute the largest instance in Table 3 was 445 ± 32 s. This instance contains 30,000 deliveries. Figure 6 displays the route obtained by 2-opt. A crop of the result appears in Figure 7.

Respectively, instances 78 and 79 contain 40 and 50 thousand deliveries. The weighted matrix has $40{,}000^2$ and $50{,}000^2$ elements. The largest instance contains 2.5 billion of longs, each long with 8B, resulting in a matrix of 20GB of memory. This large matrix doesn't fit in the computer memory. It is necessary to compute the weight w_{ij} at runtime by a shortest path algorithm, thus increasing execution time. The results using a shortest path instead of w_{ij} can be seen in Table 4. The results obtained are nearly the same as in Table 4, but the time to find the result increased. The time is about ten times larger, considering instances 72 and 75.

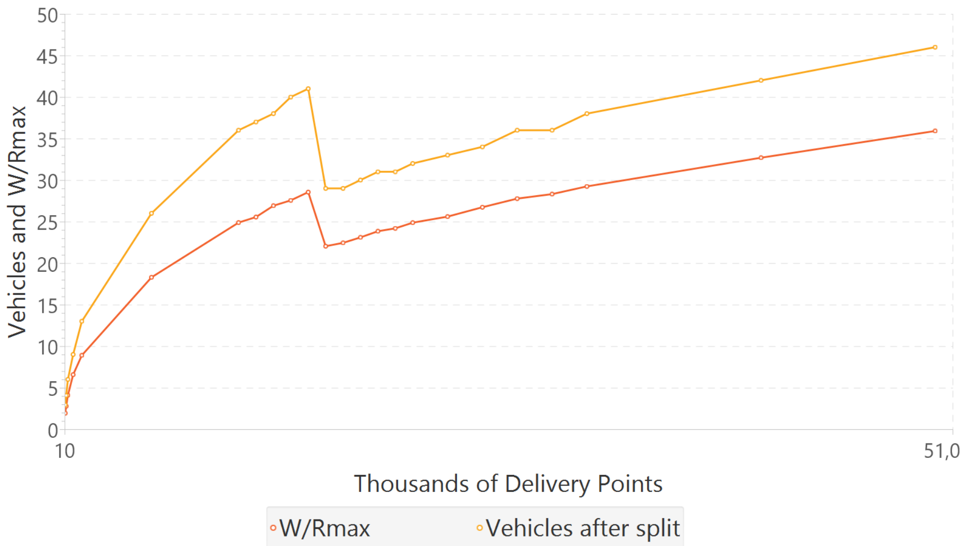

Figure 5 – Number of vehicles or W/R_{max} × Number of deliveries of instances in thousands. The W/R_{max} (red line) is obtainable by dividing the total length after the optimization by the value of R_{max}. The vehicles (yellow line) were obtained through the division of routes by the greedy algorithm.

Table 4 – RioClaroPost results. Results obtained calculating the w_{ij} by shortest path algorithm. Results were obtained through five executions for each instance. Results are similar to Table 3, except for the time, which is larger here.

ID	#Deliveries	W/R_max avg±std	#vehicles avg±std	time(s) avg±std
72	28000	28.28±0.06	36.2±0.4	3054±203
75	30000	29.25±0.07	37.8±0.4	4256±599
78	40000	32.79±0.06	42.2±0.4	4566±266
79	50000	35.87±0.07	46.0±0.0	8055±630

6 CONCLUSION

In this research we model new multi-objective instances to the benchmark PostVRP (Meira et al., 2020) for mail deliveries on foot in the city of Rio Claro. At the end, the generated model has 1,674 streets.

Each street receives a classification, which is used for the distribution of delivery points. The classification follows the patterns used in the original instances (Meira et al., 2020). In total, 80 instances were generated, containing from three deliveries and three vehicles up to 50,000 deliveries and 120 vehicles. The instances generated in this research is open for use.

The benchmark generated in this research is open for use under request.

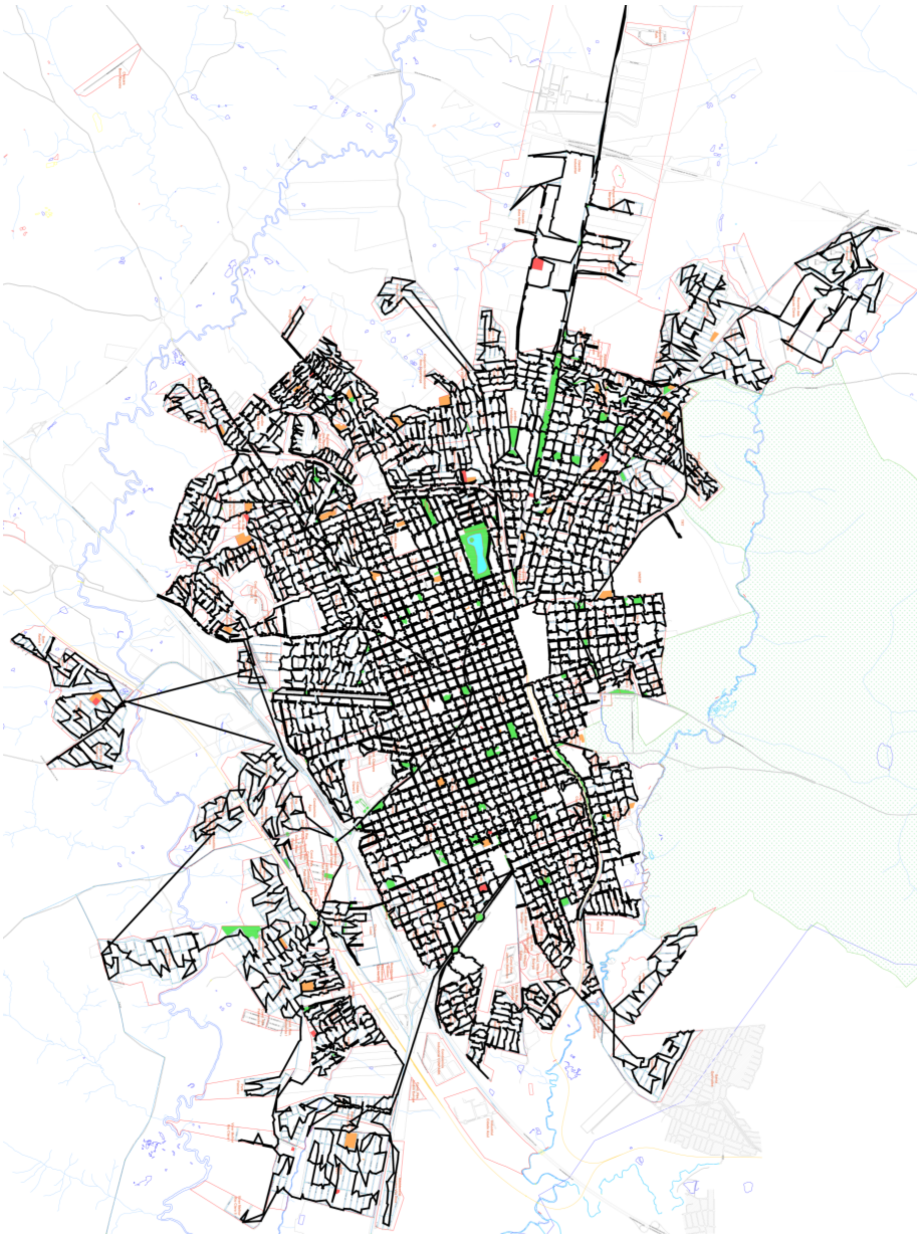

Figure 6 – Result obtained by the optimization of the instance RioClaroPostChristmas_30000_0 by the 2-opt algorithm. It contains one route.

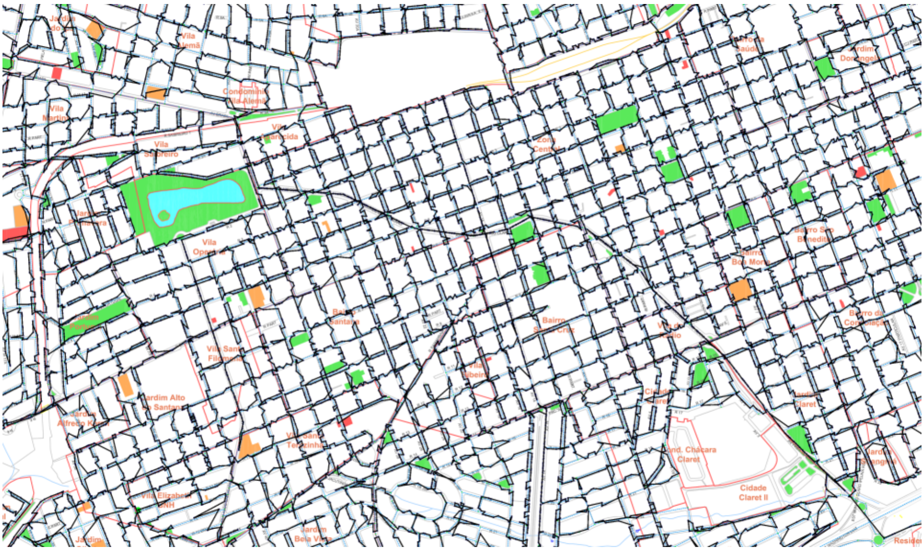

Figure 7 – Result obtained by the optimization of the instance RioClaroPostChristmas_30000_0 by the 2-opt algorithm. The optimization was based in only one route. Cut from the central region.

Acknowledgments

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