

Routing Vehicles for Dengue Control

Matheus Diógenes Andrade

matheusdiogenesandrade@gmail.com

Institute of Computing - University of Campinas

Cidade Universitária Zeferino Vaz - Barão Geraldo, Campinas - SP, 13083-970

Fábio Luiz Usberti

fusberti@ic.unicamp.br

Institute of Computing - University of Campinas

Cidade Universitária Zeferino Vaz - Barão Geraldo, Campinas - SP, 13083-970

Rafael Kendy Arakaki

rafael.arakaki@ic.unicamp.br

Institute of Computing - University of Campinas

Cidade Universitária Zeferino Vaz - Barão Geraldo, Campinas - SP, 13083-970

RESUMO

Este trabalho¹ propõe uma metodologia exata para o roteamento de veículos nebulizadores para a visita de regiões com focos de dengue. A metodologia é fundamentada em uma formulação de Programação Inteira (PI) para o Problema do Carteiro Rural. Experimentos computacionais foram conduzidos sobre um conjunto de instâncias do mundo real da cidade de Campinas, São Paulo, obtidas pelo Open Street Maps. Os resultados mostram que a metodologia é eficaz na obtenção de rotas ótimas para instâncias com mais de 2500 vértices e 5500 arcos em menos de uma hora de tempo computacional.

PALAVRAS CHAVE. Dengue, Problema do Carteiro Rural, Pesquisa Operacional.

ABSTRACT

This work² proposes an exact methodology for routing spraying vehicles during the visit of regions with dengue outbreaks. The methodology is grounded on an Integer Programming (IP) formulation for the Rural Postman Problem. Computational experiments were conducted over a set of real-life instances from the city of Campinas, São Paulo, obtained from the Open Street Maps. The results show that the methodology is effective to obtain optimal routes for instances with more than 2500 vertices and 5500 arcs in less than one hour of computational time.

KEYWORDS. Dengue. Rural Postman Problem. Operations Research.

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1. Introduction

In the Americas, between the epidemiological week (EW) 1 of 2020 and EW 21 of 2020, a total of 1,645,678 cases of arboviral diseases were reported. Among those 1,600,947 (97.3%) were dengue cases with a cumulative incidence rate of 164.18 cases per 100,000 people. Also, 37,279 were Chikungunya cases, and 7,452 were Zika cases [WHO, 2020a]. Only in Brazil, a total of 1,040,481 cases of dengue were reported from which 585 (0.05%) were classified as severe, 342 deaths, and 20,986 remained under investigation [WHO, 2020a].

Figure (1) presents a graph that shows the number of Dengue, Chikungunya, and Zika cases in the Americas from 2008 to 2020.

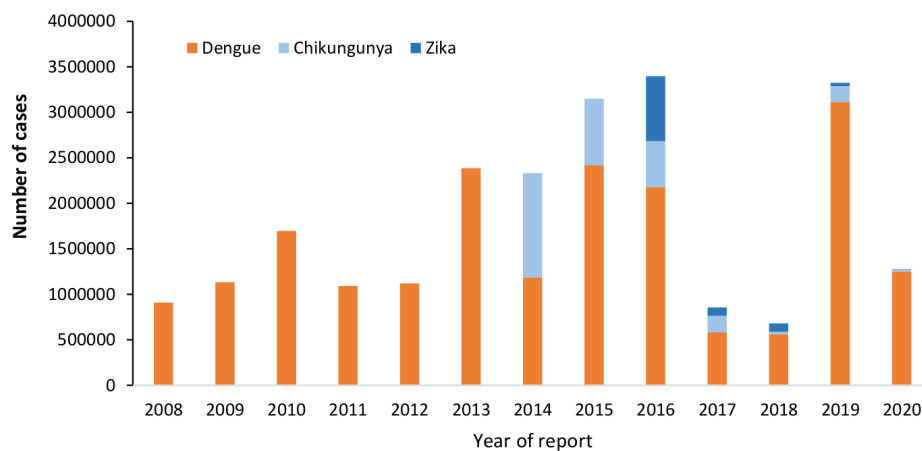


Figure 1: Dengue, Chikungunya, and Zika reported cases in the Americas from years, 2008-2020 (up to EW 21 of 2020) [WHO, 2020a].

Dengue control is an activity with several external factors, which are decisive for both the disease and its mosquito-spread. Among these factors, the urban agglomerations stand out: inappropriate housing conditions, water supply irregularity, and improper residue disposal [Brazilian Department of Health, 2009].

Concerning mosquito control, the first step of the activities plan is to identify and enumerate the streets blocks targeted for insecticide spraying. The Global Positioning System facilitates the location of blocks and properties, playing an important role to support mosquito control. Many types of equipments are used for killing the mosquitoes, for example, vehicles attached to an insecticide spraying. The insecticide spraying must be complementary to other control actions, given its limited effectiveness when used alone and high environmental impact. Nonetheless, spraying vehicles are very efficient, due to their high performance (80 to 160 blocks per day). The insecticide spraying application must be constantly supervised to guarantee the appropriate ingredient dosage on each traversed block, since there may be interference from several operational factors, such as the equipment flow, wind velocity, and the vehicle speed [Brazilian Department of Health, 2009]. Figure 2 shows the side and back view of a spraying vehicle.



(a) Spraying vehicle side view.



(b) Spraying vehicle back view.

Figure 2: Spraying vehicle examples [Brazilian Department of Health, 2009].

Figure 3 presents an example of a route that visits four blocks of a street.

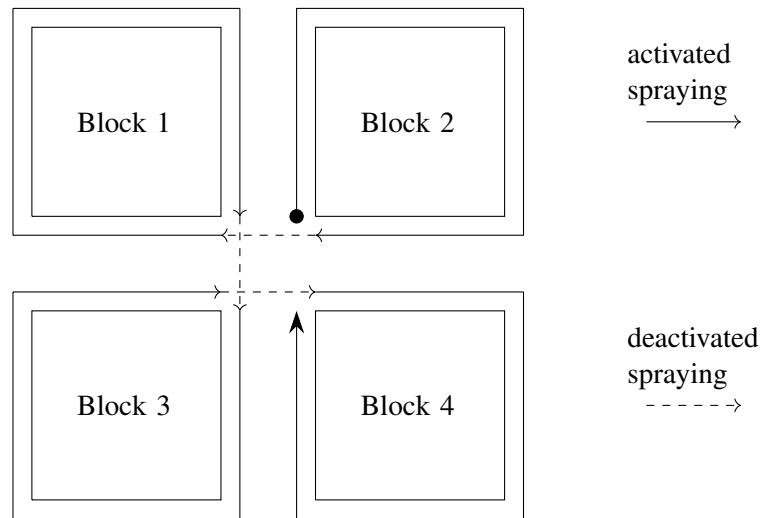


Figure 3: Route of a spraying car visiting four blocks of a street.

The COVID-19 pandemic is placing immense pressure on health care and management systems worldwide. Notwithstanding the impact of COVID-19, there is a crucial need to sustain efforts to address dengue and other arboviral diseases in the framework of the Integrated Management Strategy for prevention and control of arboviral diseases (IMS-arbovirus), which includes management, epidemiology, patient care, laboratory, integrated vector management, and environment [WHO, 2020a]. With dengue transmission levels under control, the health system is alleviated from additional strain, given that the available health resources, as staff, equipment, and supplies are likely to be diverted to provide a response to the COVID-19 epidemic.

Countries are encouraged to continue epidemiological surveillance and provide reports of suspected and confirmed dengue cases. Since clustering of cases is common in both diseases (dengue and COVID-19), efforts must be made to analyze the spatial distribution of cases to enable a rapid local-level response of the most affected areas. Prior information on hotspots of dengue should be targeted for intensive control of the mosquito-spread [WHO, 2020a].

Source reduction of mosquito breeding sites and adult mosquito control measures should be implemented in areas affected by or at risk of dengue. Spatial application of insecticides is necessary with the aim of rapidly eliminating the adult mosquito population and reducing dengue transmission. WHO prequalified insecticides, preferably based on evidence of susceptibility of the local population of *Aedes*, are recommended [WHO, 2020b,a].

In this work, we propose a Rural Postman Problem (RPP) IP formulation to obtain a minimum cost route for the spraying vehicles. Plenty of works approached the thematic of machine learning and dengue [Carvajal et al., 2018; Scavuzzo et al., 2018; Hair et al., 2019; Appice et al., 2020]. Carvajal et al. [2018] study compares the predictive accuracy of the temporal pattern of Dengue incidence in Metropolitan Manila as influenced by meteorological factors (flood, precipitation, temperature, southern oscillation index, relative humidity, wind speed, and direction) from four modeling techniques, (a) General Additive Modeling, (b) Seasonal Autoregressive Integrated Moving Average with exogenous variables, (c) Random Forest, and (d) Gradient Boosting. And concluded that relative humidity is an important meteorological factor along with rainfall and temperature that can influence the temporal pattern.

Scavuzzo et al. [2018] includes the temporal modeling of the oviposition activity (measured weekly on 50 ovitraps in a north Argentinean city) of *Aedes aegypti*, based on time series of data extracted from satellite images. They employ machine learning models that have the advantages of being non-parametric and capable of describing nonlinear relationships between variables, by assessing a support vector machine, an artificial neural network, a K-nearest neighbors, and a decision tree regressor. Compared to linear models used in previous works with similar datasets for generating temporal predictive models, the proposed methods performed better than linear approaches. In particular, the nearest neighbor regression (KNNR) performs the best. These results provide better alternatives to be implemented operatively on the Argentine geospatial risk system, a system that uses satellite data from geospatial technologies to address Dengue epidemiological problems, by generating spatial and temporal predictive risk models based on satellite-derived environmental conditions.

Hair et al. [2019] propose the use of machine learning as a tool to identify the possible characteristics that could be used to develop a risk criterion for severity in dengue patients. They analyzed the clinical profiles of 523 confirmed dengue cases to identify clusters of patients with similar patterns. The findings suggest that age must be the first characteristic to be considered in places where dengue is hyperendemic, and that warning signs should be closely monitored, mainly in children.

Similar to [Carvajal et al., 2018], Appice et al. [2020] formulate a holistic machine learning strategy to analyze the temporal dynamics of temperature and Dengue data and use this knowledge to produce accurate predictions on an annual time frame. The temporal dynamics are extracted from historical data by utilizing a novel multi-stage combination of auto-encoding, window-based data representation, and trend-based temporal clustering, and the prediction is performed with a trend association-based nearest neighbor predictor. The effectiveness of the proposed strategy is evaluated in a case study that comprises the number of Dengue and Dengue hemorrhagic fever cases collected over the period from 1985 to 2010 in 32 federal states of Mexico. The study proves the viability of the proposed strategy and confirms that it outperforms various state-of-the-art competitor methods formulated both in regression and in time series forecasting analysis.

Although there are plenty of works applying operations research techniques for the Dengue mosquito control [Reis et al., 2018; Florentino et al., 2018; de O. Florentino et al., 2018], to the best of our knowledge only three papers apply operations research techniques for the context of routing problem along with the mosquito control [Negreiros et al., 2008, 2011, 2020], and its noteworthy that among these papers only two present approaches for the spraying vehicles routing. Negreiros et al. [2008, 2011] give a Periodical Scheduling of Vehicles in Areas integer programming formulation, and [Negreiros et al., 2011] give a GRASP heuristic for the spraying vehicles routing. Negreiros et al. [2011] apply the proposed algorithm in a small instance corresponding to the location

of Praia de Iracema, Fortaleza.

Our work, inspired by the methodology of [Negreiros et al., 2011], takes a step forward by proposing an exact methodology for routing spraying vehicles that is capable of solving large real-life instances, with more than 2500 vertices and 5500 arcs.

This work is organized as follows. Section 2 presents the proposed formulation. Section 3 shows the computational experiments detailing the instance generation procedure and the benchmark results. Section 4 contains the work final remarks.

2. Methodology

Let $D(V, A)$ be a digraph, where V is the set of vertices and A is the set of arcs, $A_R \subseteq A$ is the set of required arcs that must be visited, and c_a the arc a cost. An RPP solution is composed of a minimum cost closed walk that visits all the arcs in A_R . In this work, we compact the minimum cost path between every pair of distinct vertices in $V(A_R)$ to a single arc with cost equals to the cost of the shortest path between them. Formally, we consider a digraph $D'(V(A_R), A_R \cup \{(i, j) : (i, j) \notin A_R \wedge i, j \in V(A_R)\})$, and we set $c'_a = c_a$ if $a \in A_R$, and $c'_{(i,j)} = c(P_{ij})$ if $(i, j) \in A(D') \setminus A_R$, where P_{ij} is the shortest path between the vertices i and j in D .

Below is presented an IP formulation for the problem. Let $x_a \in \mathbb{N}$ be the number of times arc a is visited in a solution.

$$\min \sum_{a \in A(D')} x_a c'_a \quad (1)$$

$$\text{s.t.} \quad \sum_{a \in \delta^+(i)} x_a = \sum_{a \in \delta^-(i)} x_a \quad \forall i \in V(A_R) \quad (2)$$

$$x_a \geq 1 \quad \forall a \in A_R \quad (3)$$

$$\sum_{a \in \delta^+(S)} x_a \geq 1 \quad \forall S \subset V(A_R) : S \neq \emptyset \quad (4)$$

$$x_a \in \mathbb{N} \quad \forall a \in A(D') \quad (5)$$

The objective function (1) minimizes the solution total cost. Constraints (2) impose the number of entering arcs in a vertex to be the same as the number of exiting arcs. Constraints (3) force every mandatory arc to be visited at least once. The set of constraints (4) ensures the solution connectivity by obligating every non-empty proper subset of vertices in $V(A_R)$ to have at least one outgoing arc in its cut. And finally, the constraints set (5) defines the variable domain constraints.

3. Computational experiments

3.1. Instance generation

New instances were generated based on real dengue outbreaks locations in the city of Campinas, São Paulo [Campinas City Hall, 2021]. From those, five contain a single connected component induced by A_R . The Open Street Map (OSM) tool [OpenStreetMap contributors, 2017] was used to obtain the street topology of the locations. The set of arcs A' represents the streets of the region under consideration while the set of required arcs A_R represents the streets with reported outbreaks. For every pair of distinct nodes in $V(A_R)$, all the arcs in the shortest path using the haversine distance, a formula that determines the great-circle distance between two points on the globe given their longitudes and latitudes, between them in A' were selected, and their union with A_R resulted in A .

The Algorithm 1 gives the steps to generate an ARPP instance.

Algorithm 1: Instance generation algorithm

Input: The region arcs A' , and the outbreaks arcs A_R
Result: A feasible RPP instance
 Let $D(V(A_R), A_R)$ be the RPP instance containing the arcs in A_R and their respective vertices;
for $i \in V(A')$ **do**
 for $j \in V(A')$ **do**
 if $i \neq j$ **then**
 $P \leftarrow$ the i - j shortest path in A' ;
 $A(D) \leftarrow A(D) \cup A(P)$;
 $V(D) \leftarrow V(D) \cup V(P)$;
 end
 end
end
return D ;

The above algorithm was implemented in Julia v1.3.1 [Bezanson et al., 2017]. The machine used for the executions was an Intel(R) Xeon(R) CPU E5-2630 v4 @ 2.20GHz, with 64 GB of RAM, and Linux 4.15.0-74-generic Ubuntu x86_64 GNU/Linux. Table 1 presents the selected locations, the number of required and non-required arcs, the number of vertices, and the total distance of required arcs in kilometers for every instance. All of the selected locations were chosen based on reported outbreaks [Campinas City Hall, 2021].

Instance	Location	$ A_R $	$ A - A_R $	$ V $	A_R^{Km}
1	Jardim Campos Elíseos and Jardim Paulicéia	1772	816	1036	85.27
2	Jardim Maria Rosa, Jardim Telesp, Jardim Itatinga, and Parque São Paulo	1383	157	677	63.57
3	Jardim Bela Vista	838	1116	907	22.99
4	Parque da Fazenda, Jardim Roseira, and Vila Perseu Leite de Barros	1512	742	929	57.58
5	Swiss Park and Jardim Nossa Sra de Lourdes	494	634	523	20.88
6	Vila San Martin, Parque Cidade Campinas, and Residencial Campo Florido	736	286	422	37.26
7	Instances 1 and 2 locations	3105	1757	2097	148.85
8	Instances 3 and 6 locations	1574	2722	1973	60.25
9	Instances 4 and 5 locations	1988	3602	2536	78.43

Table 1: Location, $|A_R|$, $|A| - |A_R|$, and $|V|$ of every instance.

Note that instances 7 to 9 were generated as compositions of instances 1 to 6 locations.

3.2. Computational results

The IP formulation presented in Section 2 was implemented with the JuMP 0.18 [Lubin e Dunning, 2015] library, and solver CPLEX 12.9 [Cplex, 2009] using the academic license. The fractional and integer separation algorithm of the constraints (4) was implemented as a BFS graph traversal to identify the connected components and include their corresponding constraints.

Table 2 presents the computational results for each instance. The column Cost corresponds to the vehicle traversed distance in kilometers. The column LP gives the root node linear programming relaxation in kilometers, after adding the cuts of constraints (4). The column Time contains the IP model execution time in seconds. The column Deadheading presents the vehicle deadheading traversed distance in kilometers. The column Route time presents the solution traversed time in hours. We consider a 10 Km/h velocity for required edges, and a 40 Km/h velocity for deadheading. The column #B&B nodes gives the explored number of branch-and-bound nodes. The column #B&B integer shows the explored number of branch-and-bound integer nodes. The column Cuts gives the number of identified violated constraints (4).

Instances			Cost(Km)	LP(Km)	Deadheading(Km)	Route time(h)	Time(s)	#B&B nodes	#B&B integer	Cuts
#	$ A_R $	$ A - A_R $								
1	1772	816	89.14	89.14	39.24	8.62	3.86	1	1	3
2	1383	157	65.42	65.42	15.30	6.40	1.85	1	1	3
3	838	1116	30.02	26.87	71.05	2.47	7.03	12	4	41
4	1512	742	62.11	62.11	19.68	5.87	4.53	1	1	3
5	494	634	34.62	34.62	0.64	2.43	13.73	1	1	1
6	736	286	40.37	40.37	3.40	3.79	3.11	1	1	5
7	3105	1757	163.20	162.42	687.92	15.24	14.35	4	2	16
8	1574	2722	97.94	92.76	37.69	6.96	910.26	27	4	112
9	1988	3602	107.85	106.25	29.42	8.57	2659.93	213	4	15

Table 2: Computational results.

As we can see the proposed method was effective for the instances containing a single connected component induced by A_R , and obtaining optimal solutions even for the larger instances with more than one connected component (instances 5 and 7). The relatively low number of cuts and branches corroborates on the model tightness. Even though the RPP is a representative of NP-hard problems, these experiments show that typical instances generated from urban topologies can still be tackled by exact approaches.

Figures 4-12 show the instances regions and their respective solutions.



Figure 4: Instance and solution for the outbreak locations Jardim Campos Elíseos and Jardim Paulicéia.

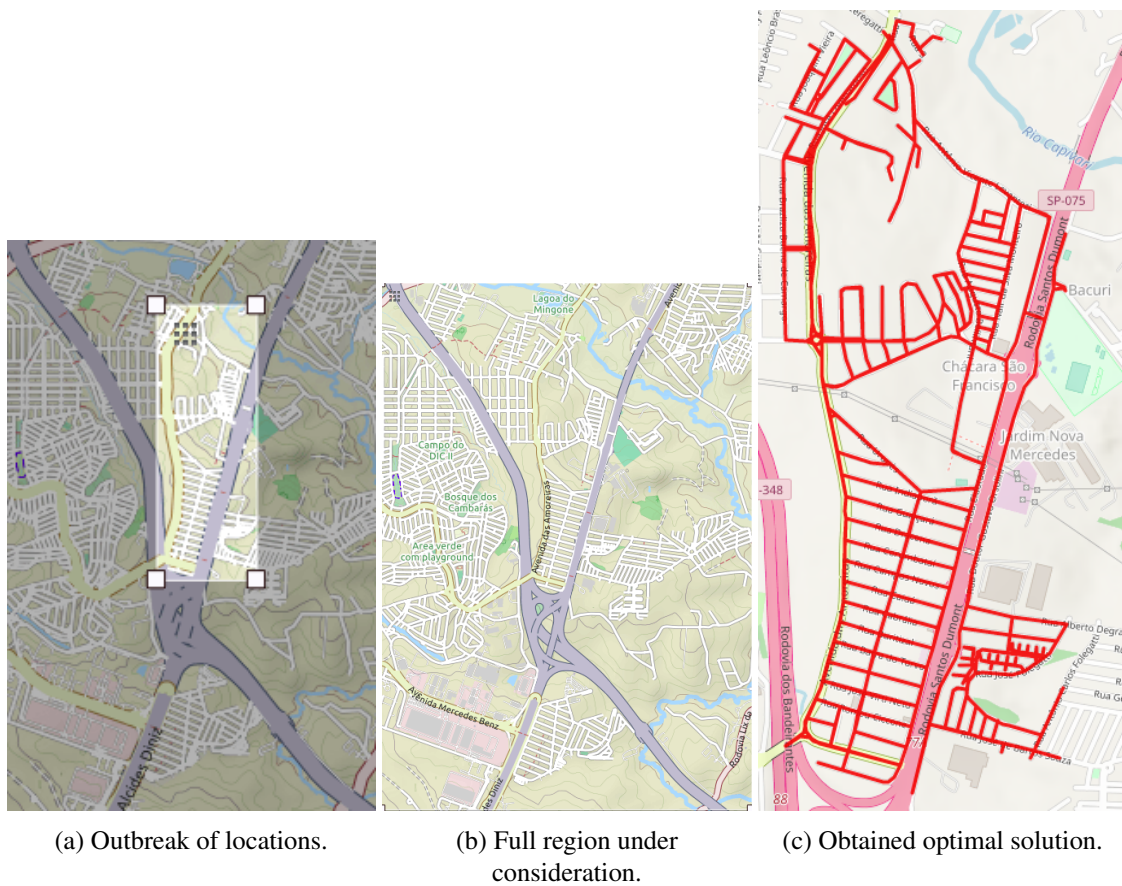


Figure 5: Instance and solution for the outbreak locations Jardim Maria Rosa, Jardim Telesp, Jardim Itatinga, and Parque São Paulo.

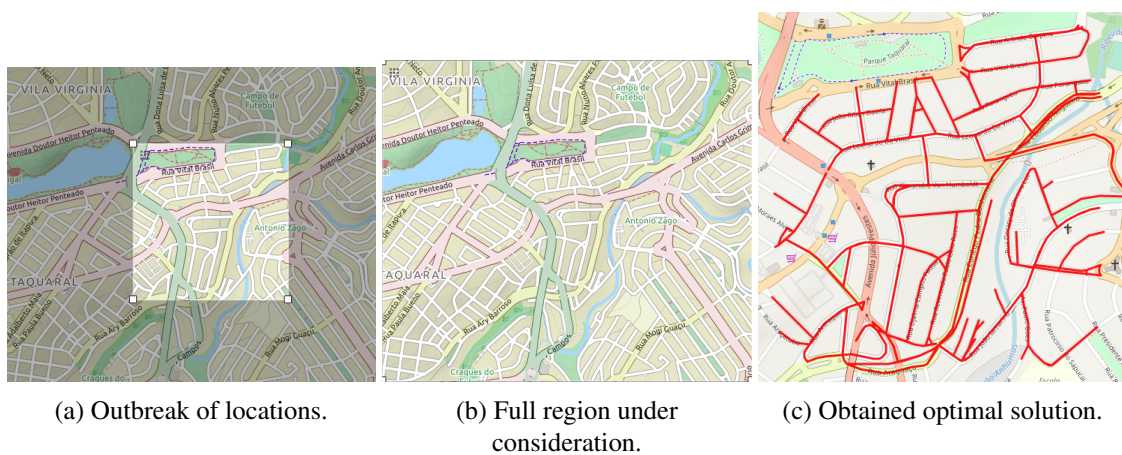
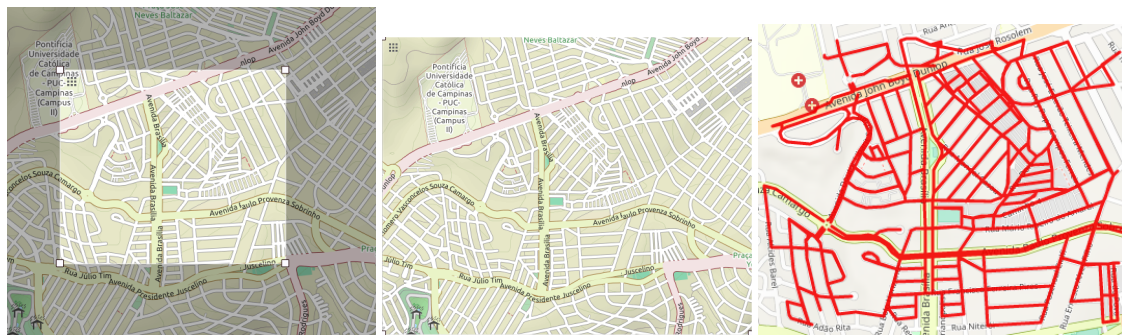


Figure 6: Instance and solution for the outbreak locations Jardim Bela Vista.

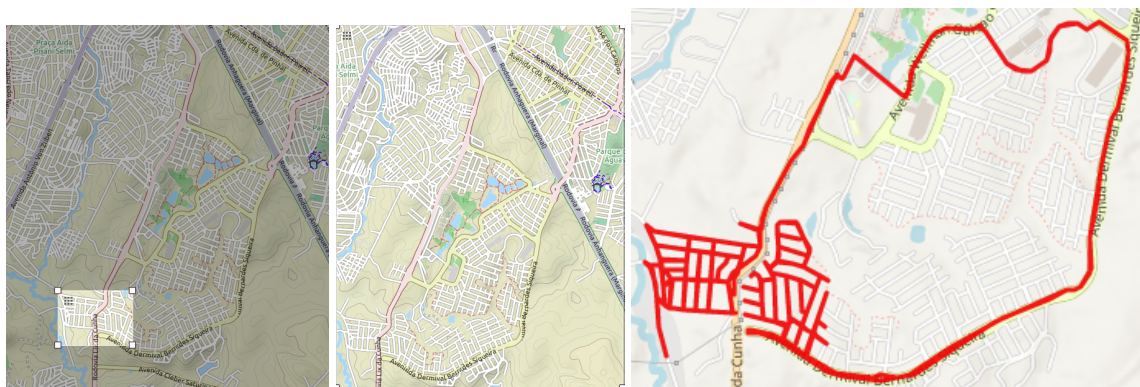


(a) Outbreak of locations.

(b) Full region under consideration.

(c) Obtained optimal solution.

Figure 7: Instance and solution for the outbreak locations Parque da Fazenda, Jardim Roseira, and Vila Perseu Leite de Barros.

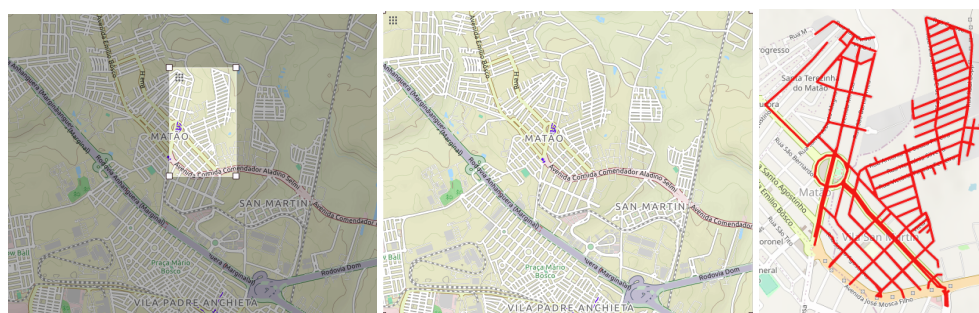


(a) Outbreak of locations.

(b) Full region under consideration.

(c) Obtained optimal solution.

Figure 8: Instance and solution for the outbreak locations Swiss Park, and Jardim Nossa Sra de Lourdes.

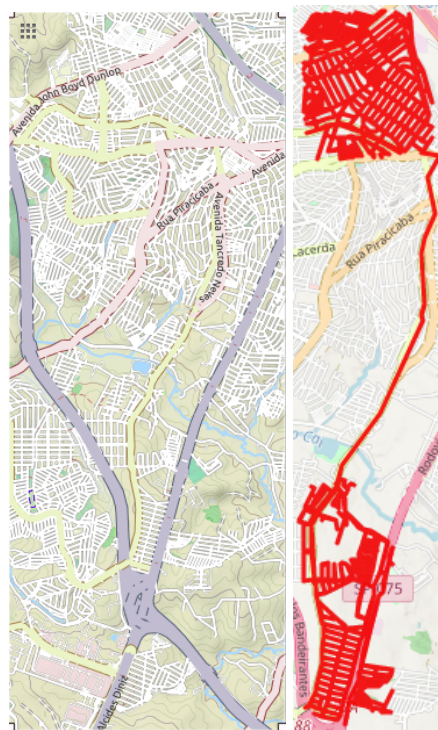


(a) Outbreak of locations.

(b) Full region under consideration.

(c) Obtained optimal solution.

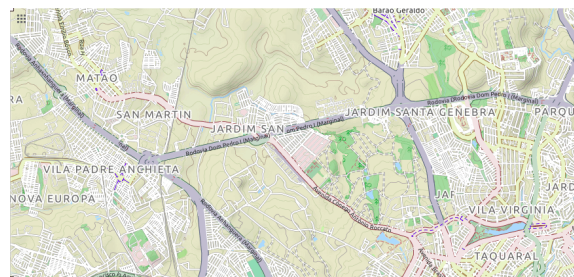
Figure 9: Instance and solution for the outbreak locations Vila San Martin, Parque Cidade Campinas, and Residencial Campo Florido.



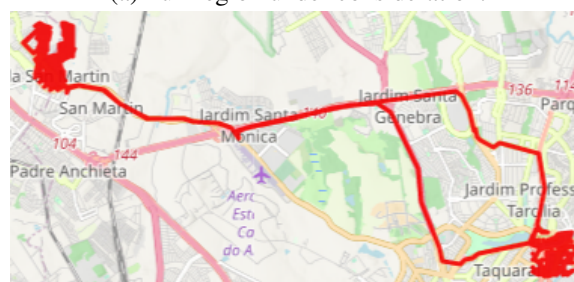
(a) Full region under consideration.

(b) Obtained optimal solution.

Figure 10: Instance and solution for instance 7 outbreak locations.



(a) Full region under consideration.



(b) Obtained optimal solution.

Figure 11: Instance and solution for instance 8 outbreak locations.

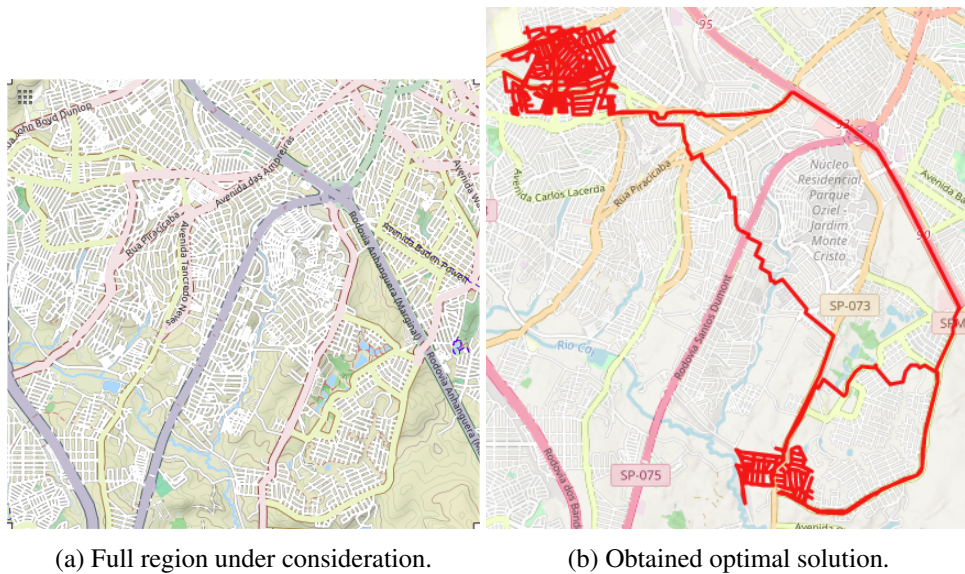


Figure 12: Instance and solution for instance 9 outbreak locations.

4. Final Remarks

In this work, we proposed a formulation and an exact methodology to route nebulizer vehicles for visiting dengue outbreak regions. The proposed methodology has a high potential for reducing the routing costs, therefore contributing to the more efficient allocation of resources concerning the control of arboviral disease, which is especially relevant in municipalities with highly constrained budgets.

As future work, the machine learning state-of-the-art methods can be employed to generate more comprehensive instances. Furthermore, there are additional constraints that can be considered, such as the vehicle time limit, the vehicle insecticide tank capacity, and time windows. We thank the referees for their feedback that allowed us to improve the paper.

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