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SAMU AMBULANCE POSITIONING USING MALP MODEL

Ormeu Coelho[1], Fernando Alexandrino[1], Bruno Barreto[1]

1 Federal Center for Technological Education Celso Suckow da Fonseca – CEFET/RJ

ABSTRACT

One of the constitutional principles of the public health care system in Brazil is universality, which turns health into a fundamental right and ensures that all citizens shall have access to health service whenever required. The purpose of this study is to assess the positioning of ambulances in Duque de Caxias-RJ, and find new arrangements to maximize the covered population. The configuration of a network that provides such service is indeed significant since small deviations may lead to users' death. Therefore, four scenarios were built in order to represent different network arrangements, according to the manager's strategy or the budget limitations of the city. An Integer Programming model for servers' positioning was used in each scenario. Indicators such as percentage of coverage population and total cost were then used to compare and choose the best solution. Results have shown that the current coverage could be doubled by just relocating facilities that already exist, without adding any costs. It is important to notice that this solution is rather different from the current positioning.

Keywords: facility location; emergency services; Integer Programming; ambulance positioning.

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1. INTRODUCTION

In the public sector, particularly in health care, one of the logistics problems of greatest interest is the ambulances' location, in order to create an emergency care network. The location of this kind of facility is quite sensitive to the required service level, mainly characterized by the service response time, since a poor coverage may result in the death of the user of this service. Bertelli *et al*. (1999) say that the highest frequency of survival in cardiac arrest victims occurs when the resuscitation maneuvers are carried out within 8 minutes.

Thus, it can be found in the literature plenty papers that use optimization techniques in order to design a network that maximizes coverage or minimizes the response time. For instance, Eaton *et al*. (1985) saved $3.4 million in construction costs in Austin (Texas), while, in Bangkok, Fujiwara *et al*. (1987 reduced the total number of ambulances from 21 to 15, keeping the average response time and, more recently, Takeda *et al*. (2004) reduced the average travel time by only repositioning ambulances.

According to the Brazilian Health Ministry, the *Serviço de Atendimento Móvel de Urgência* (SAMU - Mobile Emergency Care Service) system covered 70.9% of Brazilian population in 2012 (Ministério da Saúde, 2013). Besides, SAMU's policy also allows the decision maker to create decentralized operational bases for ambulances and their teams, using headquarters' infrastructure or the minimum essential space for a proper work. This paper is mainly based on this concept, as will be seen further.

Duque de Caxias is a city in the metropolitan region of Rio de Janeiro that has 464,619 square kilometers of land area and 855,048 inhabitants, distributed among 40 districts (IBGE, 2010). They are grouped in four regions: Duque de Caxias, Campos Elíseos, Imbariê and Xerém. The city has only 9 ambulances to provide cover for its population, which is almost one ambulance for each 100,000 inhabitants.

The current study aims: (i) to analyze the service level of the current disposition of ambulances in the city; (ii) to propose new logistics arrangements through the use of optimization models for increasing the system's coverage; and (iii) to compare the alternative solutions obtained by the optimization model. In order to accomplish these goals we have analyzed four scenarios, which give the decision maker alternatives that can be chosen according to the city's policies. In each scenario new arrangements are proposed for positioning the ambulances, increasing the coverage, even when lacking budget.

This paper was organized into 5 sections. Section 2 presents a brief literature review on emergency location models, thus allowing a proper selection of a model adherent to our application. Section 3 details the way data have been acquired and how the mathematical model was applied to them. The results obtained for each scenario are discussed in Section 4 and compared to the current situation. Finally, Section 5 sums up the achievements and considerations of this study for future research.

2. LITERATURE REVIEW

When it comes to emergency service location and relocation models, it is possible to find plenty of models in the literature, which have been developed over the last 30 years (Brotcorne *et al*., 2003). Despite each model's particularity, the coverage of the users by servers within a predefined response time is a common requirement for all of them.

Coverage problems such as this are usually defined over a valued graph , such that each node in represents a demand point and/or a potential location for the ambulances. The set of edges represents the urban road network through these nodes. There is a positive real number indicating a distance/time for crossing edge . Given a pair of nodes and , a demand node is covered by a server located in node if, and only if, the distance or travel time between these nodes is less than or equal to a coverage limit, , i.e. . Thus, is the set of sites that cover demand point .

The most incipient models, regarding ambulance, location is the Location Set Covering Model (LSCM), proposed by Toregas *et al.* (1971) and Maximal Covering Location Problem (MCLP), introduced by Church *et* ReVelle (1974). While LSCM aims to minimize the number of vehicles needed to cover all demand points, MCLP tries to maximize population coverage by means of a given limited number of ambulances.

However, such models are not suitable to deal with traffic jam. As pointed out by Galvão *et al*. (2003a), in congested systems, ambulances can be busy among 20% and 30% of the time, thus requiring any sort of modeling of that probabilistic behavior. The usage of backup servers is a possible strategy for increasing the service level. Following these ideas, Hogan *et* ReVelle (1986) introduce BACOP1 and BACOP2 models. The authors use two different binary variables to indicate the coverage of a demand point by one or two servers, respectively.

Later, Schilling *et al*. (1979) come up with a model called Tandem Equipment Allocation Model (TEAM) that couples with two different types of vehicles. Usually, health emergency systems operate with two types of vehicles: basic life support (BLS), which is able to serve basic emergencies, since it is equipped with a limited number of instruments;

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and advanced life support (ALS), which is equipped to deal with severe cases. In Brazil, BLS is used for patients who do not need medical intervention during the transport, while ALS assists high risk patients who need intensive medical care (Ministério da Saúde, 2006). In TEAM, each type of vehicle has its own coverage limit, given by or , such that and are, respectively, the set of sites that cover the demand point by a BLS and an ALS. TEAM aims to maximize covered demand covered by both kinds of ambulances.

Gendreau *et al.* (1997) introduce the Double Standard Model (DSM) based on the concept of multiple coverage: all demand points should be covered by an ambulance to a time less than and a rate of the requests should also be met by another ambulance in units of time . This response time is limited by Ball *et* Lin (1993) to, at most, 10 minutes in urban areas with , and may be augmented to 30 minutes in rural areas, according to United States regulations. At the beginning of the last decade in London, 95% of the requests should be answered within 14 minutes; however, there was no limit on (Galvão *et al.*, 2003b).

All previous formulations are deterministic whereas the usage of probabilistic models is an evident research direction in these kinds of applications. The Maximum Expected Covering Location Problem proposed by Daskin (1983) assumes that all facilities have the same probability of being busy (the busy fraction). Therefore, given a node covered by ambulances, the expected covered demand is defined by . It is important to note that more than one ambulance may be located at the same node (Brotcorne *et al.*, 2013).

The Maximum Availability Location Problem (MALP) was presented by ReVelle and Hogan (1989) in two different versions, which differ from each other according to the busy fraction imposed to each type of ambulance. Galvão *et al.* (2003a) explain that MALP I assumes that all servers have the same busy fraction . On the other hand, in MALP II the busy fraction is computed to each server, thus resulting in specific values for each geographic area. The authors note that MALP II requires a simulation model, or anything similar, in order to compute specific rates for each server according to the solutions. ReVelle and Hogan (1989) also attest that MALP II is more complex, since the busy fraction is an output of the model and cannot be known *a priori*. Both models deal with stochasticity under simplifying assumptions.

MALP I aims to locate P ambulances so that the greatest number of calls to a particular emergency service always have a server to answer them within a distance/time of no more than with reliability (Galvão *et al.*, 2003a). Daskin (1983) defines the busy fraction as shown in (1).

$$\rho = \frac{\bar{t}\sum_{j \in J}\phi_j}{24\sum_{i \in I} x_i} = \frac{\bar{t}\sum_{j \in J}\phi_j}{24\,P} \tag{1}$$

where:

ϕ_j = the total of calls during one day at node ;

$\bar{t}$ = the average time for answering a call (in hours);

P = the number of servers.

Furthermore, constraint (2) defines that, at least, one vehicle must be available to a demand node $j \in J$ for a distance/time of, at most, T, with probability of, at least, θ.

$$P(\text{if at least one server is within } T) \geq \theta \Leftrightarrow$$

$$1 - \rho^{\alpha} \geq \theta \tag{2}$$

where:

$\alpha = \sum_{i \in I} c_{ij} x_i$ is the number of servers available at a maximum distance T from a given demand node $j \in J$;

c_{ij} = the entries of the binary matrix, which assumes 1 whenever $t_{ij} \leq T$, and 0, otherwise.

As the desire is to cover a specific area with reliability θ, there must be, at least b, servers able to attend this area as shown in (3).

$$\sum_{i \in I} c_{ij} x_i \geq b \tag{3}$$

such that $b = \lceil \log(1-\theta)\,/\,log\rho \rceil$.

It means that, for each demand point j, there must be, at least, b servers within T so that it can be covered with reliability θ. Thus, in order to maximize the number of calls that are answered with the given reliability, one can maximize the number of calls with, at least, b servers available within T (Galvão *et al.*, 2003a). Thus, consider the following decision variables:

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$$x_i = \begin{cases} 1, \text{if an ambulance is located at node } i; \\ 0, \text{otherwise.} \end{cases}$$

$$y_j = \begin{cases} 1, \text{if node } i \text{ is covered by, at least, } b \text{ servers;} \\ 0, \text{otherwise.} \end{cases}$$

MALP I formulation, as defined by Mohorosi (2008), is given in (4)-(7).

$$\text{Maximize} \quad \sum_{j \in J} \phi_j y_j \qquad (4)$$

$$\text{Subject to:} \quad \sum_{i \in I} c_{ij} x_i \geq b y_j \qquad \forall j \in J \qquad (5)$$

$$\sum_{i \in I} x_i = P \qquad (6)$$

$$x_i, y_j \in \{0,1\} \qquad i \in I, j \in J \qquad (7)$$

The objective function (4) maximizes the total calls along all demand points. Constraint (5) ensures that a node j is covered only when there are, at least, b ambulances within a distance of, at most, T. Equation (6) specifies the number of ambulances to be located. Along the following section the MALP I, a formulation is used for evaluating possible positioning strategies for SAMU ambulances in the city of Duque de Caxias-RJ.

3. DATA MODELING

The previous literature review suggests that MALP I is the most suitable model, according to our main proposal: maximize coverage while taking into account the effect of server's congestion. The application of this model to the data obtained from the Duque de Caxias's ambulance system assumes a partition of the geographical area of the city into 48 nodes: 22 nodes are related to sites where there already exists an infrastructure for ambulance location (such as hospitals or emergency units), while the others 26 refer to districts in which the city is divided, but do not have such structure. The same population distribution of the city's districts was adopted, according to information acquired through the census carried out by IBGE in 2010 (IBGE, 2010). When there was more than one allocation candidate site at the same district, the population was divided equally between them. For instance, Xerém district has 3 candidate sites for ambulance location. Therefore, this district's population has been divided by 3 and each site turned into a node with its own ZIP code and specific demand.

Through an interview with the operational coordination of SAMU in Duque de Caxias, hospitals, health clinics and UPAs (emergency units) in the city were identified as candidate points for receiving a facility without fixed installation costs. In the remaining districts, a ZIP code was arbitrarily chosen, and the installation costs were estimated according to information provided by real estate market companies. The following ZIP codes have been randomly chosen according to the district zone. Table 1 describes the nodes of the network considered in the study, such that the shaded ones are those where installation costs are null.

The total cost for installing each new facility was estimated by: (i) a fixed cost for building and equipping sites (28m² for every building); (ii) a variable cost accord to the number of ambulances to be located at the facility (20m² for each ambulance). Table 2 shows the estimated costs of a new facility in each district. While the first column refers to fixed costs, the second one is presented as the cost per ambulance, as it is related to the area occupied by each server.

In this study the number of calls was replaced by the number of inhabitants in the geographical area of node , . In the lack of historical calls to SAMU data system in Duque de Caxias, this is a reasonable simplifying assumption in terms of the distribution of emergency calls along population in a long term analysis. The population of each node and its geographic coordinates (latitude – LAT – and longitude – LONG) can be found in Table 3.

The travel time between a facility and demand point , , in minutes, was computed, taking into account the geographical coordinates of these nodes and the urban infrastructure for mobility. A simple VBA code was then used for recovering the routes and the travel time between and , with the support of Google Maps API. Once travel time is usually higher during rush hours, samples of the travel time were taken between 5 and 7 pm, in order to simulate the worst traffic condition. Table 4 shows the average of these samples, such that the shaded ones are those where .

4. ALTERNATIVE NETWORK CONFIGURATION

This section was split into two parts. First, the current network configuration is presented, followed by its attendance statistics. After that, four alternative configurations for the SAMU network were analyzed by changing a few premises, representing different management strategies. All experiments were made, assuming a coverage limit minutes and ambulances of BLS type. Moreover, the required confidence level θ was 80%, which corresponds to coverage of a demand node by, at least, $b = 3$ servers.

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Table 1. Network nodes

Description	Node	Description	Node
Pam 404 Doutor Fernando Gil	01	Duque de Caxias, CEP 25250-400	25
Posto de Saúde Alaide Cunha	02	Duque de Caxias, CEP 25271-350	26
Duque de Caxias, CEP 25235-460	03	Duque de Caxias, CEP 25036-600	27
Duque de Caxias, CEP 25015-415	04	Duque de Caxias, CEP 25272-410	28
Duque de Caxias, CEP 25267-390	05	Duque de Caxias, CEP 25265-232	29
Posto Médico Sanitário de Campos Elíseos	06	Hospital Municipal Dr. Moacir R. do Carmo	30
Duque de Caxias, CEP 25220-570	07	Duque de Caxias, CEP 25240-650	31
Duque de Caxias, CEP 25245-230	08	Duque de Caxias, CEP 25046-380	32
Centro Municipal de Saúde de Duque de Caxias	09	Posto de Saúde Sarapuí	33
Hospital Infantil Ismélia Silveira	10	UPA Sarapuí	34
UPA Infantil Walter Garcia	11	Duque de Caxias, CEP 25025-300	35
UPA Duque de Caxias	12	Posto Médico Sanitário do Pilar	36
Duque de Caxias, CEP 25251-100	13	Posto Médico Sanitário Santa Cruz da Serra	37
Duque de Caxias, CEP 25243-150	14	Duque de Caxias, CEP 25271-430	38
Duque de Caxias, CEP 25237-030	15	Duque de Caxias, CEP 25040-060	39
Posto Médico Sanitário Parque Equitativa	16	Duque de Caxias, CEP 25045-040	40
Duque de Caxias, CEP 25060-190	17	Posto Médico Sanitário Saracuruna	41
Duque de Caxias, CEP 25231-180	18	Duque de Caxias, CEP 25270-450	42
Posto Médico Sanitário Dr. Jorge R. Pereira	19	Duque de Caxias, CEP 25030-180	43
Posto de Saúde Doutor José de Freitas	20	Duque de Caxias, CEP 25040-610	44
Posto de Saúde Edna Salles	21	Duque de Caxias, CEP 25065-162	45
Posto de Saúde José Camilo dos Santos	22	Hospital Municipal Maternidade de Xerém	46
Hospital Estadual Adão Pereira Nunes	23	Unidade Pré-Hospitalar Álvaro Figueira	47
Duque de Caxias, CEP 25250-130	24	Posto Médico Sanitário de Xerém	48

Source: The authors' own

Table 2. Installation costs

Node	Fixed cost (R$)	Variable cost (R$/m²)	Node	Fixed cost (R$)	Variable cost (R$/m²)
03	107,100.00	1,325.00	27	104,608.00	1,236.00
04	135,545.67	2,340.92	28	135,545.67	2,340.92
05	113,988.00	1,571.00	29	135,545.67	2,340.92
07	135,545.67	2,340.92	31	135,545.67	2,340.92
08	135,545.67	2,340.92	32	135,545.67	2,340.92
13	130,676.00	2,167.00	35	135,545.67	2,340.92
14	143,360.00	2,620.00	38	135,545.67	2,340.92
15	135,545.67	2,340.92	39	135,545.67	2,340.92
17	166,432.00	3,444.00	40	135,545.67	2,340.92
18	135,545.67	2,340.92	42	124,852.00	1,959.00
24	135,545.67	2,340.92	43	116,676.00	1,667.00
25	135,545.67	2,340.92	44	135,545.67	2,340.92
26	135,545.67	2,340.92	45	162,652.00	3,309.00

Source: The authors' own

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Table 3. Population distribution

Node	LAT	LONG	αj	Node	LAT	LONG	αj
01	-22.793	-43.299	7,071	25	-22.596	-43.302	10,616
02	-22.786	-43.297	7,071	26	-22.626	-43.206	2,344
03	-22.676	-43.357	6,477	27	-22.766	-43.328	34,770
04	-22.795	-43.326	41,209	28	-22.629	-43.210	14,458
05	-22.638	-43.244	15,700	29	-22.657	-43.230	4,444
06	-22.660	-43.250	19,622	30	-22.799	-43.289	44,983
07	-22.688	-43.236	13,053	31	-22.635	-43.307	8,161
08	-22.647	-43.328	1,489	32	-22.725	-43.319	34,969
09	-22.787	-43.308	6,756	33	-22.751	-43.296	1,009
10	-22.788	-43.311	6,756	34	-22.751	-43.299	1,009
11	-22.793	-43.307	6,756	35	-22.779	-43.324	17,898
12	-22.786	-43.325	6,756	36	-22.711	-43.306	33,525
13	-22.657	-43.274	14,120	37	-22.645	-43.274	25,698
14	-22.665	-43.315	14,085	38	-22.625	-43.210	16,732
15	-22.630	-43.222	2,460	39	-22.745	-43.317	11,420
16	-22.635	-43.263	33,501	40	-22.728	-43.305	22,062
17	-22.764	-43.299	43,996	41	-22.676	-43.254	46,660
18	-22.680	-43.298	16,520	42	-22.627	-43.236	12,191
19	-22.636	-43.217	34,332	43	-22.774	-43.313	21,922
20	-22.637	-43.231	12,867	44	-22.742	-43.317	31,009
21	-22.761	-43.278	53,731	45	-22.773	-43.298	30,420
22	-22.695	-43.261	20,915	46	-22.599	-43.302	7,466
23	-22.670	-43.279	20,915	47	-22.600	-43.292	7,466
24	-22.598	-43.293	192	48	-22.601	-43.292	7,466

Source: The authors' own

The computational experiments described in this section were computed in a notebook Dell Inspiron 14R 3350 model with Intel Core™ i5 processor, operating system Windows 7 Ultimate 64-bit and 6GB of RAM. The Integer Program (1)-(8) model was coded in AIMMS (Advanced Integrated Multidimensional Modeling Software) version 4.0 and optimized by CPLEX 12.6.

4.1 Current scenario analysis

As in many Brazilian cities, the positioning of ambulances of the SAMU system in Duque de Caxias is made empirically, without the support of any computational tool. This often leads to an increase in the response time and the probability of losing calls due to low confidence level. Table 5 shows the current positioning of ambulance in the city.

The coverage for this configuration was computed according to MALP's premises and, thus, no distinction has been established between basic and advance ambulances, in order to keep homogeneity required by this model. Therefore, only 37.9% of the population is covered within 12 minutes for $\theta = 8\ \%$. It follows that almost two thirds of the citizens are not covered to the required service level. The current distribution of servers is shown in Figure 1, which shows the 22 vertices with no location costs. Spots with smaller diameter are nodes which have the structure for ambulance location but there is no ambulance currently, while those ones with larger diameter represent a node where there is a server positioned.

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Table 4. Average travel time (in minutes)

Node	01	02	06	09	10	11	12	16	19	20	21	22	23	30	33	34	36	37	41	46	47	48
01	02	04	24	03	08	05	13	23	24	23	12	20	16	07	11	12	16	22	23	23	22	22
02	04	04	22	05	08	07	10	21	22	21	10	18	14	09	09	10	14	20	21	22	20	20
03	27	26	28	25	23	24	27	23	28	27	27	29	20	28	19	19	15	22	29	16	16	16
04	10	11	27	08	06	08	04	26	27	26	16	23	19	13	15	16	19	25	26	26	25	25
05	27	26	09	29	29	30	33	06	10	05	22	22	13	23	24	25	23	08	14	17	15	15
06	18	18	29	20	20	21	25	13	18	18	14	11	10	15	15	16	15	12	05	13	12	11
07	27	26	30	29	29	30	34	24	30	29	22	10	23	23	24	25	23	23	10	25	23	23
08	26	26	20	28	29	29	33	15	20	19	21	21	13	23	23	25	19	14	21	13	13	12
09	04	05	26	03	08	07	10	25	26	25	14	22	19	09	13	13	19	25	25	26	25	24
10	07	08	28	05	01	04	06	27	28	27	16	24	21	12	13	13	19	26	27	28	26	26
11	09	11	25	07	04	02	09	24	25	24	14	21	18	10	13	14	17	23	24	25	23	23
12	09	09	29	08	05	08	07	28	29	28	17	25	21	14	15	15	22	27	28	28	27	27
13	18	18	12	20	20	21	25	07	12	11	14	14	04	15	15	17	15	03	13	12	10	10
14	25	25	19	27	27	28	32	14	19	18	21	20	11	22	22	23	18	13	20	15	13	13
15	26	26	08	28	28	29	33	09	02	06	22	20	16	23	23	24	23	11	13	20	18	18
16	25	24	11	27	27	28	32	05	10	06	20	20	12	21	22	23	21	06	16	15	14	13
17	12	08	21	09	11	11	13	20	21	20	09	17	14	10	06	06	14	19	20	21	19	19
18	21	21	15	23	25	26	29	14	15	14	17	16	07	18	18	19	13	13	16	15	13	13
19	25	24	06	27	26	27	31	11	04	05	20	18	18	21	22	23	21	13	11	19	18	18
20	25	24	06	27	26	27	31	07	05	04	20	18	14	21	22	23	21	09	11	18	16	16
21	12	11	21	14	14	14	19	20	22	21	03	17	14	08	08	09	14	20	21	21	20	20
22	21	20	24	23	22	23	27	20	24	23	16	09	16	17	18	19	16	19	08	21	19	19
23	17	16	09	19	19	20	24	11	09	08	13	13	16	14	14	15	13	07	11	13	11	11
24	25	25	19	27	27	28	32	13	19	19	21	20	12	22	22	23	22	13	20	03	02	02
25	26	26	21	29	28	29	33	14	21	20	22	22	13	23	24	25	23	14	21	02	03	03
26	27	26	08	29	28	29	33	12	04	08	22	20	19	23	24	25	23	14	13	21	20	20
27	15	14	33	14	11	14	08	32	33	32	22	29	25	20	14	14	21	31	32	32	31	31
28	26	25	08	28	28	29	33	12	03	07	21	19	19	22	23	24	22	14	13	20	19	19
29	23	22	05	25	25	26	30	13	06	07	18	16	15	20	20	21	19	15	10	18	16	16
30	05	08	22	07	08	08	13	21	22	21	11	18	15	06	10	11	14	20	21	22	20	20
31	27	27	22	29	29	30	34	13	22	18	23	23	14	24	25	26	25	12	22	08	07	07
32	15	15	22	14	12	13	16	21	23	22	16	23	15	17	08	08	08	20	23	21	20	20
33	13	13	18	11	10	10	14	17	18	17	08	14	11	09	02	02	11	17	18	18	17	16
34	13	13	20	11	09	10	14	19	21	20	09	16	13	10	02	01	13	19	20	20	19	19
35	11	10	30	10	07	10	04	29	30	29	18	26	23	16	16	16	24	29	30	30	29	28
36	20	20	18	19	17	17	21	16	18	17	20	20	11	21	13	13	05	16	19	17	16	16
37	21	20	13	23	22	24	27	05	13	11	16	16	07	17	18	19	17	02	15	12	11	10
38	27	27	09	29	29	30	34	11	04	09	22	20	19	24	24	25	23	14	14	22	21	21
39	14	13	25	13	10	11	15	24	25	24	14	21	18	15	07	07	14	24	24	25	24	23
40	16	15	25	14	13	13	16	23	25	24	16	23	17	17	08	08	10	22	25	23	22	22
41	21	20	21	23	23	24	28	15	21	20	16	08	13	17	18	19	17	14	06	15	14	14
42	28	28	13	30	30	31	35	07	08	07	24	23	15	25	25	26	25	10	17	18	17	17
43	09	06	27	06	05	06	07	26	27	26	15	23	20	13	11	11	18	25	26	27	25	25
44	15	15	28	13	12	13	16	26	28	27	15	22	20	16	08	08	13	25	26	27	25	25
45	09	05	21	06	08	09	11	20	21	20	09	17	13	09	08	09	13	19	20	21	19	19
46	26	26	20	28	28	29	33	14	20	20	21	21	13	23	23	24	22	13	21	01	03	03
47	25	24	19	27	27	28	32	13	19	18	20	20	11	21	22	23	21	13	19	03	04	01
48	24	24	18	26	26	27	31	12	18	18	20	19	11	21	21	22	20	11	19	03	01	04

Source: The authors' own

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Table 5. Ambulances current distribution

Node	Location	ALS	BLS
06	Posto Médico Sanitário de Campos Elíseos		1
16	Posto Médico Sanitário Parque Equitativa		1
30	Hospital Municipal Doutor Moacir Rodrigues do Carmo	2	2
36	Posto Médico Sanitário do Pilar		1
41	Posto Médico Sanitário Saracuruna		1
48	Posto Médico Sanitário de Xerém		1

Source: The authors' own

Proposed scenarios

Four planning scenarios were built in order to evaluate the impact of the redistribution of ambulances along the same or the new candidate locations. By enforcing the usage of the same set of candidate nodes of the original configuration, the decision maker searches an improved solution without the need of new investments. Thus, it is a more conservative approach. Later, the model is allowed to position the ambulances in any of the 48 nodes considered in the study. The solution produced by the MALP I model, in the absence of any budget limitation, corresponds to the best solution attainable by a set of 9 ambulances. The placement of more than one ambulance in the same node was also evaluated, once managers tend to disperse the ambulances along the network as an attempt of increase coverage, regardless of the congestion effects. First, the decision variables were defined binary, as in the original MALP I formulation, and then changed to nonnegative integers to allow the positioning of more than one ambulance per node. Table 6 summarizes the characteristics of the scenarios.

Table 6. Proposed scenarios

Scenario	Budget Constraint	Location variable
Scenario 1	Zero Investment	
Scenario 2	Relaxed	
Scenario 3	Zero Investment	
Scenario 4	Relaxed	

Source: The authors' own

The optimal solutions found for each scenario are shown in Table 7, in which the shaded lines indicate these nodes, where there is already infrastructure capable of receiving one or more ambulances. Note that, even in scenarios where the budget constraint is relaxed, the opening of new

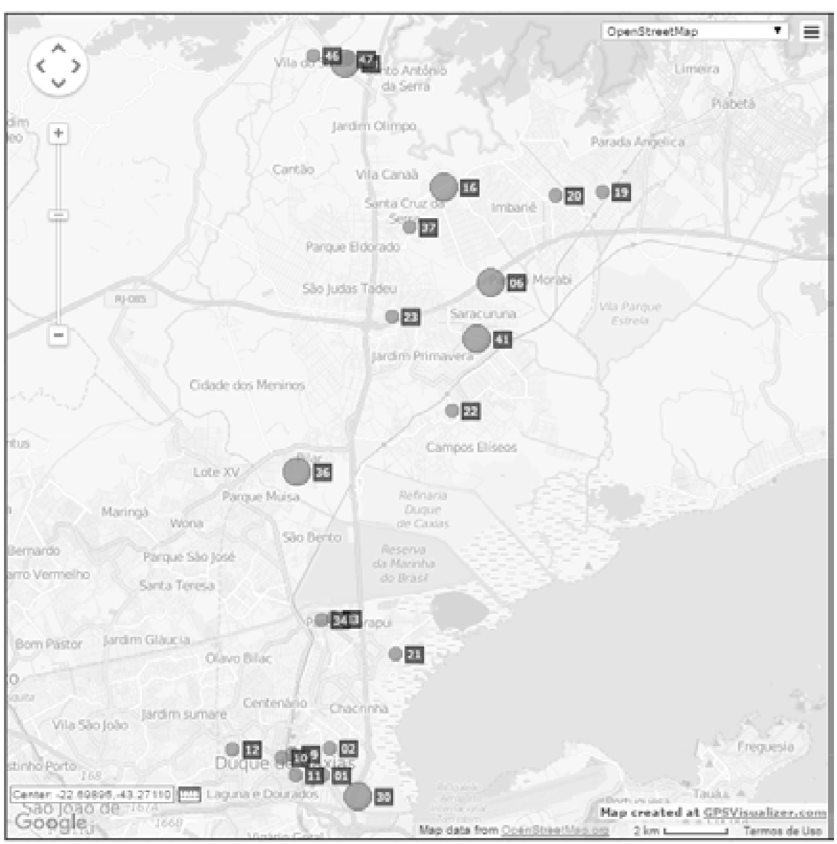

Figure 1. Current distribution of ambulances
Source: The authors' own

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facilities is not fully used by the model, being requested three times in scenario 2 (nodes 08, 13 and 17) and only once in scenario 4 (node 04). It is worth to point out that the current position of the servers was not chosen by the model in any of the studied scenarios, except by one ambulance located at node 16 in scenario 2. Thus, as it follows, the same set of resources (bases and ambulances) is able to provide better coverage through a quite distinct allocation of servers.

Moreover, the results suggest that nodes 23 and 33 are chosen in all tested scenarios, showing that these are strategic facilities to increase population coverage. However, they are not used in the current configuration of this logistic network, which concentrates four servers at node 4 whilst other nodes are not covered by, at least, three servers.

Table 7. Optimal distribution of ambulances in each scenario

Nodes	Current	Scenario 1	Scenario 2	Scenario 3	Scenario 4
01	-	-	-	-	-
02	-	1	-	-	-
03	-	-	-	-	-
04	-	-	-	-	3
05	-	-	-	-	-
06	1	-	-	-	-
07	-	-	-	-	-
08	-	-	1	-	-
09	-	-	-	-	-
10	-	1	-	-	-
11	-	1	-	-	-
12	-	-	-	3	-
13	-	-	1	-	-
14	-	-	-	-	-
15	-	-	-	-	-
16	1	1	-	-	-
17	-	-	1	-	-
18	-	-	-	-	-
19	-	1	1	-	-
20	-	1	1	-	-
21	-	-	-	-	-
22	-	-	-	-	-
23	-	1	1	3	3
24	-	-	-	-	-
25	-	-	-	-	-
26	-	-	-	-	-
27	-	-	-	-	-
28	-	-	-	-	-
29	-	-	-	-	-
30	4	-	-	-	-
31	-	-	-	-	-
32	-	-	-	-	-
33	-	1	1	3	3
34	-	1	1	-	-
35	-	-	-	-	-
36	1	-	-	-	-
37	-	-	1	-	-
38	-	-	-	-	-
39	-	-	-	-	-
40	-	-	-	-	-
41	1	-	-	-	-
42	-	-	-	-	-
43	-	-	-	-	-
44	-	-	-	-	-
45	-	-	-	-	-
46	-	-	-	-	-
47	-	-	-	-	-
48	1	-	-	-	-

Source: The authors' own

Another interesting result is the smaller number of used bases in scenarios 3 and 4 that clearly favors the reduction of the overall logistic cost. In both cases, two facilities received three ambulances. Comparisons among the solutions found for each scenario were based on the obtained coverage and the installation cost. The results are summarized in Table 8 together with the number of opened sites. The benefits of using an optimization technique for designing emergency service networks are expressive, enabling the care of population twice as large as the current one. And this improving is obtained by just relocating the already available ambulances.

Table 8. Indicator for each optimization scenario

Scenario	Coverage	Sites	Cost (R$)
Current	37.9%	6	0.00
Scenario 1	73.5%	9	0.00
Scenario 2	77.0%	9	591,692.00
Scenario 3	90.4%	3	0.00
Scenario 4	90.4%	3	276,000.67

Source: The authors' own

Once the binary variables decision variables in (1)-(6) have been relaxed to nonnegative integers, the solution of scenarios 3 and 4 are upper bounds of the solutions found for scenarios 1 and 2, respectively. There is a remarkable gap among solutions found for these scenarios, which emphasizes the advantage of concentrating ambulances in certain strategic nodes. It should also be noted that, among the proposed scenarios, the integer alternative (90.4% coverage – scenarios 3 and 4) is more efficient than the original MALP I (77% coverage – scenario 2), where allocation variable is binary. In other words, coverage decreases when it is forbidden to locate more than one ambulance at the same facility, forcing their dispersion along the network. It means that, in this study, the strategy that maximizes coverage population creates clusters, or partitions, at nodes, instead of using coverage intersections for different sites. Figure 2 shows geographical servers' distribution for the best configuration – scenario 3.

5. CONCLUSION

This work showed the considerable benefits of designing emergency service networks with the aid of optimization techniques. The results achieved in our case study show that the coverage of the population of Duque de Caxias could be considerably increased by just relocating the already available resources. This simple step reduces the response time of the callings received by the SAMU system in this city.

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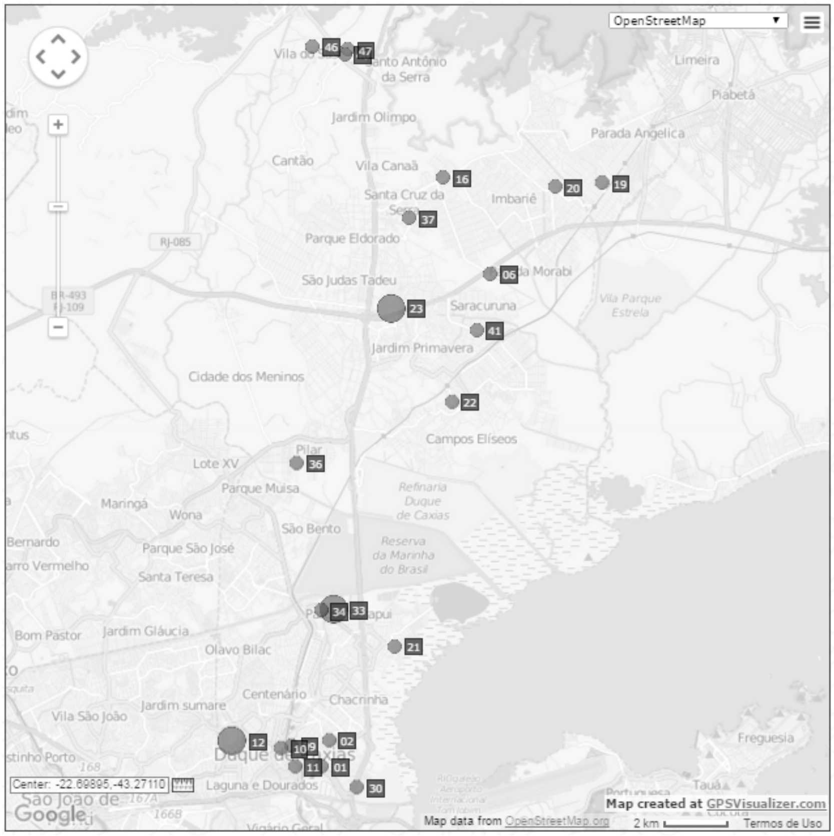

Figure 2. Distribution of ambulances on scenario 3

Source: The authors' own

The service network was modelled according the distribution of the city's districts and their respective population. Four scenarios were built to represent possible alternatives for the repositioning of the ambulances. According to the achieved results, it is possible to expand the covered population by only relocating servers along facilities already in operation. The allocation of more than one ambulance per site seems to be the most effective strategy for this real instance. Another advantage is the substantial reduction in the number of required operational sites.

The main limitations of our study refer to availability of data, making it necessary to adopt simplifications, such as modeling only one type of demand/ambulance. New studies should focus on data collection on arrival rate of callings from each demand node, as well the transit time throughout the network. The stochastic nature of such data suggests the usage of a stochastic approach. In this sense, there are possibilities as a bi-level optimization approach that integrates one model for positioning the ambulances and another to evaluate the response time under random transit times, random arrival rates and congestion effects on servers. The recent advances in Stochastic and Robust Optimization techniques also offer new possibilities for modeling and solving the problem of designing emergency service networks.

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