A clustering optimization approach for disaster relief delivery: A case study in Lima-Perú

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Abstract

During the last decade, funds to face humanitarian operations have increased approximately ten times. According to the Global Humanitarian Assistance Report, in 2013 the humanitarian funding requirement was by US$ 22 billion, which represents 27.2% more than the requested in 2012. Furthermore, the transportation cost represents between one third to two-thirds from the total logistics cost. Therefore, a frequent problem in a disaster relief is to reduce the transportation cost by keeping an acceptable distribution service. The latter depends on a reliable delivery route design, which is not evident considering a post-disaster environment. In this case, the infrastructures and sources could be inexistent, unavailable or inoperative. This paper tackles this problem, regarding the constraints, to relief delivery in a post-disaster environment (like an eight degree earthquake) in the capital of Perú. The routes found by the hierarchical ascending clustering approach, which has been solved with a heuristic model, achieved the best result.

1 Introduction

Humanitarian response recognizes two phases after a disaster: the life-saving and the life-sustaining actions (Thevenaz and Resodihardjo, 2010). The first one, consists in carrying activities that aim to preserve life, like removal debris and rescue victims. The second one, involves the provision of aid kits and services such as: food, water, temporary shelter, medical care, and protection (Assessment and Coordination, 2006). As it was mentioned in (Hall, 2012), the initial relief dispatch is more oriented to beneficiary communities in a timely manner, while waiting for the initial disaster assessment to be completed. Klibi and Martel (2012), described that under a state of disaster the depots network is not expected to respond adequately, because its storage and distribution capacity loses its nominal operability.

Moreover, Martinez et al. (2011) confirms that transport is the second largest general budget of humanitarian organizations, after staff. Thus, planning transportation routes (VRP, Vehicle Routing Problem) is one of the most important problems of combinatorial optimization and it is widely studied with many applications in the real world, like distribution logistics and transport (Toth and Vigo, 2002). The humanitarian delivery in disasters cases are concerned to optimize; maximizing unsatisfied demand, minimizing travel time and minimizing total delivery delay (Beamon and Balcik, 2008). There are three basic approaches for modeling the problem: (i) the vehicle route is represented by a binary variable of multiple indexes, that define the vehicle and route identification; (ii) the construction of a dynamic network flow model whose outputs are the vehicle and material flows, that have to be parsed in order to construct vehicle routes and loads and; (iii) to enumerate all feasible routes between all pairs of supply and demand nodes (Özdamar and Demir, 2012). The latter open a data analysis utilization based on pattern mining, data mining or clustering to optimize delivery routes. For our purposes, we decided to use the last mentioned approach.

In literature, numerous works have been proposed to deal with the problem of spatial clustering on data associated to natural disasters. Early papers attacked the problem of emergency evacuation, for example, Pidd et al. (1996) presented a spatial decision support system to emergency planning. Their approach, based on Geographical Information System (GIS) software, evaluated two issues: (i) static, processing the data from a mathematical, statistical and logical point of view and; (ii) dynamic, establish the terrain for evacuation under certain assumptions and with some specified policies. Then, in (Gong and Batta, 2007), an ambulance allocation to improve the rescue process of victims, was proposed. The authors used a spatial clustering combined with fuzzy logic in order to allocate the correct number of ambulances to each spatial objects grouped into a cluster after an earthquake.

Later, Tai et al. (2010) described a method to evacuate Shin-Hua city, Taiwan, after an earthquake. They analyze the spatial correlation between objects taking into account six indexes associated to route characteristics. Moreover, Özdamar and Demir (2012), proposed a hierarchical cluster and route procedure (HOGCR) for coordinating vehicle routing in large-scale post-disaster distribution and evacuation activities. Recently, Matthew et al. (2015) evaluated the survival Kobe-1995-earthquake manufacturing plants and their post-earthquake economic performance. They used a geographical clustering technique combined with a micro-econometric approach.

In Perú, from 1582 to 2007, occurred 47 earthquakes with magnitudes between $6.0°$ to $8.6°$ on the Richter scale. At least 10 were greater than $8.0°$ and 100% of them occurred between the center and the south coast area of Perú; where Lima is located. Leseure et al. (2010), presented the $7.9°$ earthquake in Pisco-Perú in 2007, which killed more than 500 people and affected more than 655 thousand people; who demanded water, food, shelter, clothes, etc. The assistance for victims was distributed through multiple civil defense committees, leaded by the *Instituto de Defensa Civil* (INDECI).

Despite the efforts, they could not manage a proper relief delivery, however the authors stand out the following conclusions: (i) humanitarian donations reception and transport were improvised; (ii) humanitarian aid was distributed haphazardly; (iii) duplication of supplies in some closer areas, while the more isolated ones, received partial support and; (vi) distribution of inappropriate aid relief and unfit food for consumption (rotten food, expired date drugs, etc.).

From these statements, three points can be highlighted: (1) the high risk that would suffer the Peruvian capital in a potential major earthquake due to its sociodemographic and seismic location; (2) the failed National delivery relief case described before and; (3) the importance of supplies transportation to humanitarian operations. Therefore, it is necessary to provide an optimal, efficient and resilient route design regarding the constraints of a post-disaster environment. For this purpose, we propose an approach based on the hierarchical ascending classification that seems the best option considering the expected bad conditions of the roads in a post disaster environment.

Following this brief introduction and review, the paper is organized as follows: Section 2, describes the followed methodology. Then, Section 3, exposes the medical aid relief delivery to Lima and Callao in an eventual earthquake, analyzing the Hierarchical Ascending Classification approach for humanitarian distribution. At the end, we conclude with an analysis of the solution with the lowest travel time and also some future research works are described.

2 Methodology

In order to find an approximate solution to the process of delivery humanitarian relief in Lima, we propose an efficient and resilient approach. The efficiency is related to the ability to provide the service with fewer resources, while resilience condition is related to the ability to retain the operation in time, even whether infrastructures and sources are inexistent. Our methodology is composed by the following stages:

1. Obtain the information about the actual Peruvian humanitarian system from government entities (i.e. INDECI).

2. Perform an analysis about cartography in the territory of study, to identify the most vulnerable, exposed and threatened areas.

3. Carry out a study about available models to solve the vehicle routing problem.

4. Identify the costs following a clustering approach (Hierarchical Ascending Classification-HAC).

Our goal is to identify the routes to be used for the distribution of humanitarian aid. Whereas these routes be comprised by pre-positioned by

INDECI warehouses which are: the Medical Supplies (AM, “Almacén de Insumos Médicos”, in spanish) and Central Warehouses (AC, “Almacén Central”, in spanish); both located in Lima and pre-defined by INDECI. We follow a heuristic called “cluster-first route-second”, which determines clusters of customers compatible with vehicle capacity and solves a traveling salesman problem for each cluster (Prins et al., 2014). Thus, for this proposal we apply the Hierarchical Ascending Classification, forming clusters using the total adjusted travel time for each route instead of the Euclidean distance as a proximity measure. In order to correct this time, we use as criterion “how critical is the condition of the affected region”, which is based on measures of vulnerability, accessibility, exposure and proximity for each district of Lima, where each AM is located.

3 Results and Discussion

The HAC analysis performed by using dendrograms (Villardón, 2007), is as an efficient tool for the cluster identification task which combines many features. For instance, it is possible to separate the population into homogeneous clusters (low within-variability and high between variability). In this proposal, we have considered five features that describe vulnerabilities: (i) seismic location; (ii) socioeconomic state; (iii) access to delivery point; (iv) exposure to hazards and; (v) proximity to the central depot (AC).

Step 1: we use an advanced statistical analysis tool (XLSTAT 2013.6.03) and the vulnerability scales were obtained from the INDECI categorization criteria (see Table 1). Then, based on this criteria, we obtained a summary of the value associated with each type of vulnerability and the district where they belong to, as can be seen in Table 2. However, in order to apply the HAC approach, it is necessary to standardize our values, so there is an existent correlation (see Table 3). For this purpose, we used the method of the “maximum magnitude of 1” (Justel, 2008). This means, the division of the value of each variable by its maximum value, obtaining values between 0 and 1.

Step 2: we apply the HAC method on the new standardized data, choosing which Central Warehouses (ACs) will supply store whose Medical Supplies Warehouses (AMs). This choice was based on the shortest distance from AC to AM; for instance, if the distance between AC1 and AM1 is less than the distance between AC2 and AM1, then it will supply AC1. The result can be observed in the dendrograms shown in Fig 1, where the horizontal dotted line divides the collection of points in three clusters set by AMs.

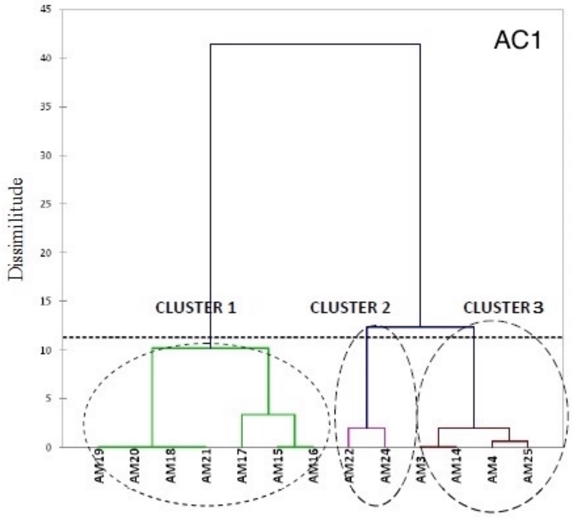
Table 1: INDECI scale values corresponding to the vulnerability type.

Socio-economic vulnerability	Night accessibility	Day accesibility
Very low (1)	Very good (1)	Very good (1)
Low (2)	Good (2)	Good (2)
Average (3)	Regular (3)	Regular (3)
High (4)	Bad (4)	Bad (4)
Very high (5)	Very bad (5)	Very bad (5)

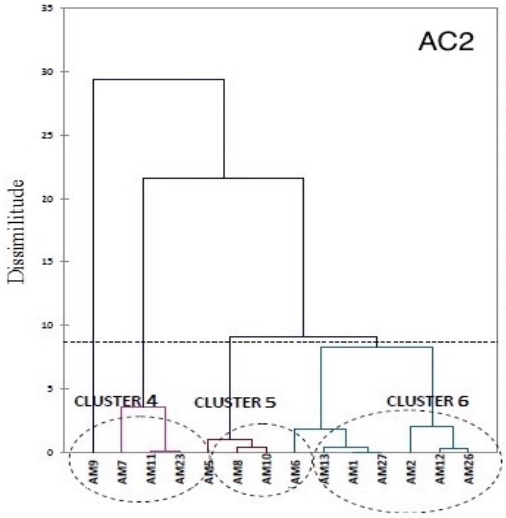
Hazards exposition	Seismic vulnerability
Low impact (1)	Low (1)
Average impact (2)	Relativity high (2)
High impact (3)	High (3)
Very high impact (4)	Very high (4)

Table 2: Summary of vulnerabilities (SE:Socio economic; DA:Day accessibility; NA:Night accessibility; HE:Hazard exposition; SZ:Seismic Zoning) for each Supply Depot and its respective Delivery Point.

Supply depots	Delivery point	Vulnerabilities					Distance AC to AM (Km)
		SE	DA	NA	HE	SZ	
AC2	AM1	2	4	1	2	1	6.29
AC2	AM2	2	4	2	5	1	6.06
AC1	AM3	2	4	3	5	2	2.06
AC1	AM4	2	4	3	4	2	1.77
AC2	AM5	2	5	3	3	1	10.21
AC2	AM6	2	4	2	1	1	2.75
AC2	AM7	2	3	1	2	2	12.54
AC2	AM8	2	5	3	2	1	8.48
AC2	AM9	1	5	4	4	1	28.32
AC2	AM10	2	5	3	1	1	9.93
AC2	AM11	2	3	2	4	2	2.44
AC2	AM12	2	4	3	3	1	1.92
AC2	AM13	2	4	1	3	1	6.43
AC1	AM14	2	4	3	5	2	1.04
AC1	AM15	1	4	4	3	1	19.78
AC1	AM16	1	4	4	3	1	19.71
AC1	AM17	1	4	2	3	1	17.44
AC1	AM18	1	4	4	3	2	21.58
AC1	AM19	1	4	4	3	2	24.37
AC1	AM20	1	4	4	3	2	24.87
AC1	AM21	1	4	4	3	2	22.87
AC1	AM22	1	3	2	4	2	5.87
AC2	AM23	2	3	2	4	2	4.60
AC1	AM24	2	3	2	4	2	3.07
AC1	AM25	2	4	2	4	2	1.13
AC2	AM26	2	4	3	4	1	0.76
AC2	AM27	2	4	1	2	1	4.96
Maximal value		2	5	4	5	2	**28.32**



AM	Cluster
AM19	1
AM20	1
AM18	1
AM21	1
AM17	1
AM15	1
AM16	1
AM22	2
AM24	2
AM3	3
AM14	3
AM4	3
AM25	3



AM	Cluster
AM9	4
AM7	4
AM11	4
AM23	4
AM5	5
AM8	5
AM10	5
AM6	6
AM13	6
AM1	6
AM27	6
AM2	6
AM12	6
AM26	6

Figure 1: Dendrograms - Clusters supplied by AC1 and AC2.

Step 3: then, we apply the algorithm proposed by Clarke and Wright (1964), looking for routes with lower cost, linking each AM to clusters. The final result shows each AM supplied by each AC, as can be seen in Table 4.

3.1 Distances Evaluation

Here, we present an analysis about post disaster distances to be covered by routes. At the beginning, Euclidean ideal distances have been considered however they must be corrected by a "Correction Factor" in order to represent realistic post disaster conditions; for example streets with debris, transport infrastructures collapsed like bridges. According to the Peruvian Ministry of Transport and Communications, the poor accessibility post disaster can cause variations up to 30 minutes (corresponding to 50% of the average transport time).

Also, reviewing historical events recorded by INDECI, it realizes that poor accessibility in affected areas increases between 25% to 100%, due to collapsed infrastructure or debris. For instance, to evaluate AM1 distance, due to correction factors, it will be increased in 65% (correction factor 165% or 1.65). Because its location has a 4 level accessibility then, corresponds to 25% and its seismic zoning characteristics corresponds to 40% (according to INDECI), hence $25\% + 40\% = 65\%$. Whether it is applied this criterion in Table 6, the corrected and covered distance (based on Table 5 percentages) for this application case is $250.32\,Km$.

Table 4: Summary routes and distances with HAC

Clusters	HAC Routes									Ideal Distance (Km)
Cluster 1	AC1	AM17	AM21	AM20	AM19	AM18	AM16	AM15	AC1	52.15
Cluster 2	AC1	AM22	AM24	AC1						12.83
Cluster 3	AC1	AM4	AM25	AM3	AM14	AC1				7.63
Cluster 4	AC2	AM9	AM7	AM11	AM23	AC2				68.93
Cluster 5	AC2	AM5	AM8	AM10	AC2					37.35
Cluster 6	AC2	AM12	AM27	AM1	AM13	AM2	AM6	AM26	AC2	21.59
										200.48

Table 3: Summary of standardized vulnerabilities (SE:Socio economic; DA:Day accessibility; NA:Night accessibility; HE:Hazard exposition; SZ:Seismic Zoning) for each Supply Depot and its respective Delivery Point.

Supply depots	Delivery point	Vulnerabilities					Distance AC to AM (Km)
		SE	DA	NA	HE	SZ	
AC1	AM3	1	0.8	0.75	1	1	0.08
AC1	AM4	1	0.8	0.75	0.8	1	0.06
AC1	AM14	1	0.8	0.75	1	1	0.04
AC1	AM15	0.5	0.8	1	0.6	0.5	0.70
AC1	AM16	0.5	0.8	1	0.6	0.5	0.70
AC1	AM17	0.5	0.8	0.5	0.6	0.5	0.62
AC1	AM18	0.5	0.8	1	0.6	1	0.76
AC1	AM19	0.5	0.8	1	0.6	1	0.86
AC1	AM20	0.5	0.8	1	0.6	1	0.88
AC1	AM21	0.5	0.8	1	0.6	1	0.81
AC1	AM22	0.5	0.6	0.5	0.8	1	0.21
AC1	AM24	1	0.6	0.5	0.8	1	0.11
AC1	AM25	1	0.8	0.5	0.8	1	0.04
AC2	AM1	1	0.8	0.25	0.4	0.5	0.22
AC2	AM2	1	0.8	0.5	1	0.5	0.21
AC2	AM5	1	1	0.75	0.6	0.5	0.36
AC2	AM6	1	0.8	0.5	0.2	0.5	0.10
AC2	AM7	1	0.6	0.25	0.4	1	0.44
AC2	AM8	1	1	0.75	0.4	0.5	0.30
AC2	AM9	0.5	1	1	0.8	0.5	1.00
AC2	AM10	1	1	0.75	0.2	0.5	0.35
AC2	AM11	1	0.6	0.5	0.8	1	0.09
AC2	AM12	1	0.8	0.75	0.6	0.5	0.07
AC2	AM13	1	0.8	0.25	0.6	0.5	0.23
AC2	AM23	1	0.6	0.5	0.8	1	0.16
AC2	AM26	1	0.8	0.75	0.8	0.5	0.03
AC2	AM27	1	0.8	0.25	0.4	0.5	0.18

Table 5: Percentage increased in distances considering each type of vulnerability.

Level	Bad Accessibility (Day and night)	Seismic Vulnerability
1	10%	25%
2	20%	50%
3	30%	75%
4	40%	100%
5	50%	–

Table 6: "Correction Factors" for each type of vulnerability and supply depot.

Supply Depot	Bad Accessibility (Day and night)	Seismic Vulnerability	Correction Factor
AM1	40%	25%	165%
AM2	40%	25%	165%
AM3	40%	50%	190%
AM4	40%	50%	190%
AM5	50%	25%	175%
AM6	40%	25%	165%
AM7	30%	50%	180%
AM8	50%	25%	175%
AM9	50%	25%	175%
AM10	50%	25%	175%
AM11	30%	50%	180%
AM12	40%	25%	165%
AM13	40%	25%	165%
AM14	40%	50%	190%
AM15	40%	25%	165%
AM16	40%	25%	165%
AM17	40%	25%	165%
AM18	40%	50%	190%
AM19	40%	50%	190%
AM20	40%	50%	190%
AM21	40%	50%	190%
AM22	30%	50%	180%
AM23	30%	50%	180%
AM24	30%	50%	180%
AM25	40%	50%	190%
AM26	40%	25%	165%
AM27	40%	25%	165%
AC1	30%	50%	180%
AC2	40%	25%	165%

3.2 Distribution Expenses Evaluation

Once we already have obtained the routes and its associated distance, it is necessary to know the type of transportation that will be used, in order to estimate the required resources. According to (Martinez et al., 2011), the best vehicles to be used in the humanitarian distribution due to its capacity and potency are the pick-up (4×4), whose main characteristics are shown in Table 7.

Table 7: Vehicle features. Source: Nissan/Toyota; UN Refugee Agency and International Federation of Red Cross and Crescent Societies.

Feature	Description
Engine power	2500 cc
Number of cylinders	4
Average performance	45 km/gal
Fuel	Diesel
Loading capacity	1 TM cc
Volume occupied by drugs	$3m^3$
Drug packaging unit	20L - 40L

According to INDECI, each medicine packaging unit (emergency backpack) should be able to supply at least two people. It is recommended an average weight of 8 Kg, corresponding to a backpack with a capacity of 20 to 40L. Thus, for practical calculations, we consider an intermediate value of 30L. Then, considering 1 vehicle, we can calculate the number of backpacks to carry and how many people they would help. For instance, every trip that makes one transport, will attend 200 people.

Backpacks = volume occupied by medicines in one vehicle; $3m^3$ = 3000L.

$$3000L \times \frac{1\text{Backpack}}{30L} = 100\text{Backpacks}$$

People = attention capacity for backpack $\times$ quantity of backpacks in one pick up

$$\frac{2\text{ people}}{\text{Backpack}} \times 100\,\text{Backpacks} = 200\,\text{people}$$

Furthermore, we proceeded to group the provinces of Lima and Callao in four main sectors: North-Lima, South-Lima, Lima-Center, East-Lima and Callao; it will allow us to estimate the amount of affected people to assist (see Table 8). Lima and Callao have 49 districts, and some of them do not have points of medical supplies depots, meanwhile other ones have more than one depot. For this reason, we consider that each depot will support the victims by the sector where they belong to (see Table 9); regardless districts which are part of it. The support must be done proportionally to victims' amount in each district.

In Table 10, we indicate the total amount of victims to be supported for each route (each clustering became to one route), considering the corrected distance according to the correction factor. Moreover, we describe the cost of fuel used to support all the victims considering the least distance covered; which is S $/.160,520.62$ approximately. We can also provide valuable additional information, for instance, the amount of trips required to support all the victims considering the number of vehicles used.

For instance, in Table 11, we obtained the number of vehicles needed to complete the route in an acceptable number of days (8.26 days), using 600 vehicles. It would support 120 000 people with 18 trips (number of trips is needed in each identified route until complete the requested demand). Finally, as an expected result, we can see in Fig 2, that the number of supported people will increase with more assigned vehicles.

Table 8: Estimated affected population in the largest Lima's districts in case a major earthquake according to (Serpa Oshiro, 2014).

District	Affected population	Sector
Ate	69954	East-Lima
Callao	195954	Callao
Carabayllo	127612	North-Lima
Chorrillos	51918	South-Lima
Comas	242235	North-Lima
Lima	18674	Lima-Center
Lurigancho	74186	East-Lima
Lurin	36312	South-Lima
Pachacamac	15260	South-Lima
Puente Piedra	144323	North-Lima
S. J. de Lurigancho	314549	East-Lima
S. J. de Miraflores	128435	South-Lima
Ventanilla	14435	Callao
Villa el Salvador	113993	South-Lima
Villa Maria del Triunfo	133171	South-Lima

4 Conclusions and Future works

In this study, we propose an approach to optimize aid distribution kits in an eventual disaster in Lima. Previous research works consider the existence of infrastructure, transport, capacity, availability of public services, among others; as a post-disaster state. However, a solution should be suitable to manage an uncertain lack of resources, lost of capacity and infrastructure. Thus, our approach using the corrected distances representing the vulnerability of a location, uses minimal re-

Table 9: Number of victims to support for each depot. Source: INEI, SIRAD.

Sector	Total victims	Depots	Total	Victims to aid for each depot
North-Lima	540 254	AM8 , AM2	2	270 127
South-Lima	483 274	AM7	1	483 274
Center-Lima	64 280	AM1, AM6, AM13 , AM27	4	16 070
East-Lima	490 985	AM5, AM9 , AM10	3	163 662
Callao	216 942	AM3, AM4, AM11, AM12, AM14, AM15, AM16, AM17, AM18, AM19, AM20, AM21, AM22, AM23, AM24, AM25, AM26	17	12 762
	1 795 735			

Table 10: Total amount of victims to be supported for each route, considering corrected distance and the cost of fuel.

Clusters	Ideal Distance (Km)	Corrected Distance (Km)	Trips	Routes	Victims treated	Fuel cost (S/.)
Cluster 1	52.15	58.54	447	Route 1	89 334	8010.36
Cluster 2	12.83	16.56	128	Route 2	25 524	656.25
Cluster 3	7.63	11.62	256	Route 3	51 048	920.97
Cluster 4	68.93	87.37	3363	Route 4	672 460	9 0967.59
Cluster 5	37.35	47.29	2988	Route 5	597 451	43 746.91
Cluster 6	21.59	28.94	1800	Route 6	359 931	16 127.55
	200.48	250.32			1 795 748	160 520.62

Table 11: Number of day trips and days to support victims (mean speed 40 kph).

Quantity of vehicles	Quantity of supported people	Total of trips (Km)	Covered distance by trip	Time (HRS)	Mean correction factor	Corrected time	Days
10	2000	899	225037.7	135022 : 36 : 29	1.76	237639 : 47 : 24	412.56
20	4000	450	112644	67586 : 24 : 00	1.76	118952 : 03 : 50	206.51
50	10 000	180	45057.6	27034 : 33 : 36	1.76	47580 : 49 : 32	82.60
100	20 000	90	22528.8	13517 : 16 : 48	1.76	23790 : 24 : 46	41.30
200	40 000	45	11264.4	6758 : 38 : 24	1.76	11895 : 12 : 23	20.65
600	120 000	18	4505.76	2703 : 27 : 22	1.76	4758 : 04 : 57	8.260

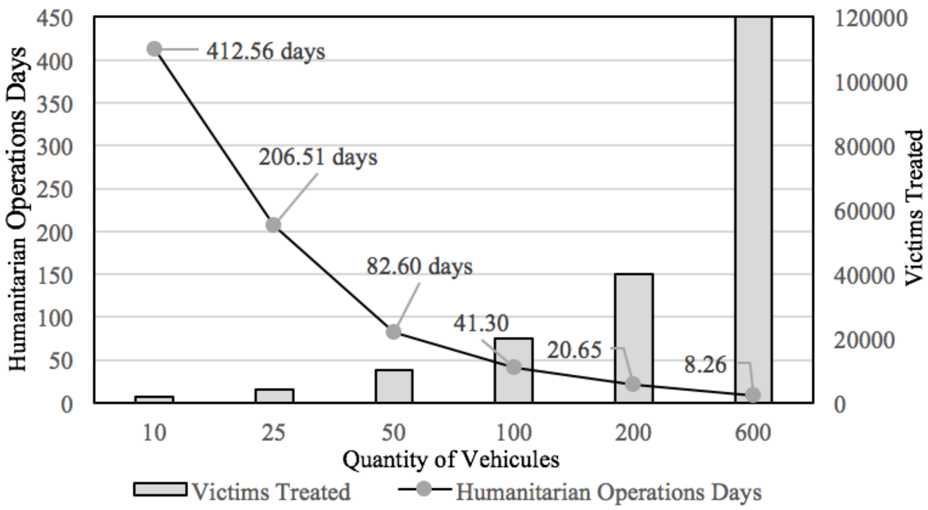


Figure 2: Number of Vehicles vs Humanitarian Operation Days and Victims Treated

sources (time to complete routes) and it is reliable (routes made under post-disaster conditions). Our results, suggests that the method of Hierarchical Ascendant Classification (HAC), allow us to find an approximate route solution, considering a post-disaster environment.

We found a sufficient and satisfactory humanitarian relief distribution, the searching solution criterion was the shortest time route with the lowest cost, under a spatial configuration which represents a post-disaster state, considering a Correction Factor (CF) to nominal times. This CF was calculated considering a previous HAC analysis, based on vulnerabilities assessment expressed by urbanistic layouts, forecast victims, seismic hazard maps, in Lima and Callao districts. For future research activities we consider to perform an evaluation adding a correction factor which use resilience assessment and; to evaluate the impact of non-considered costs as man power, maintenance, resources loading/downloading and security. In addition, to carry out a sensitivity analysis to choose particulars trucks, timetables and outsourcing service.

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