Location Optimization for Vaccination Centers of the Andean Region in Peru

Sebastian Cuya
Facultad de Ingeniería y Arquitectura
Universidad de Lima
Lima, Perú
20160433@aloe.ulima.edu.pe

Mariela Lima
Facultad de Ingeniería y Arquitectura
Universidad de Lima
Lima, Perú
20160776@aloe.ulima.edu.pe

Rosa Patricia Larios - Francia
Facultad de Ingeniería y Arquitectura
Universidad de Lima
Lima, Perú
rlariosf@ulima.edu.pe

Abstract

The COVID-19 pandemic has taken a devastating economic, social and health toll. Although vaccines have been developed to combat it, access to them was not equitable for all, especially in developing countries. Peru faces additional challenges: a tight budget, shortage of health personnel and poor health and road infrastructure. The objective of this study is to define the optimal location for vaccination centers in the most adverse regions of Peru. A mathematical model for the optimization of the location is presented taking as a reference the Set Covering, Maximal Covering and P- Median models. Coverage, location costs and travel distance were prioritized. The sample used was the district of Kimbiri in Cusco. Of the seventy rural communities and nine health centers available, 55 and 7 were included, respectively. One vaccination center was assigned per rural community. The resulting metrics were 93.6% coverage, 77.78% resource utilization and an average travel distance of 929.25 meters. This model can be used to optimize immunization processes in developing countries.

Keywords
P-median, Set Covering, Maximal Covering, Lingo, Vaccination Centers

1. Introduction
Vaccines against COVID-19 have already been developed around the world, yet accessibility is not equal to all. According to the Joint United Nations Program on HIV/AIDS (2021), by February 2021, while the vaccination ratio was about 1 person/sec in some countries, there were still countries that had not yet started their vaccination process. It is in this scenario that developing countries, including Peru, are trying to tackle the consequences of the pandemic while managing several hindrances in the vaccination process, i.e., slow access to vaccines, lack of budget, and fragile health care infrastructure (United Nations, 2020)

In their report "Estrategia para el acceso universal a la salud y la cobertura universal de salud," from 2014, the WHO recommends countries to invest at least 6% of their Gross Domestic Product (GDP) on health care; however, Peru had only made a 5.3% GDP investment by 2019 (Sociedad de Comercio Exterior del Perú, 2021), which proves a budgetary deficit in the health care sector. Additionally, health care infrastructure is very fragmented, scattered and unequal. Most tertiary care centers, the ones that belong to the highest level which include hospitals and clinics, are concentrated in the capital city, Lima (Ministerio de Salud del Perú, 2021). The inland country situation is extremely different as its infrastructure is composed of primary care centers with basic services. An aggravating factor is that the installed capacity of 97% of this establishments is not adequate (Ministerio de Salud del Perú, 2021).

Another factor to consider is the shortage of healthcare staff. There are only 13.6 physicians per every 10,000 inhabitants (Dirección General de Personal de la Salud del Ministerio de Salud del Perú, 2019) which is far below from the index recommended by OMS – 44.5 physicians per every 10,000 inhabitants (World Health Organization, 2016). Furthermore, the inequality between the capital and the inland country is noticeable. Lima has a ratio of 20.5 physicians per every 10,000 inhabitants, whereas the other regions have a significantly lower ratio (Dirección General de Personal de la Salud del Ministerio de Salud del Perú, 2019). The same is true for nursing staff where the ratio is as daunting as 15.6 nurses per every 10,000 inhabitants (Dirección General de Personal de la Salud del Ministerio de Salud del Perú, 2019).

Likewise, the precarious condition of the country's road infrastructure makes vaccine distribution more difficult leading to an increased cost. At the beginning of the pandemic, vaccines were distributed to the inland country by air and later by land. This is where the lacking adequate road infrastructure became noticeable for 86.83% of the rural roads are not paved and 98.37% of the roads in the country network are in the same condition (Ministerio de Transporte y Comunicaciones del Perú, 2019). Finally, it is worth mentioning that a considerable number of households – 75.3% – access health care centers by foot, a percentage that becomes higher in the Andean region reaching 81.8 % with an average travel time of 35 minutes at a domestic level, and almost 40 minutes in the Andean region (Instituto Nacional de Estadística e Informática, 2018).

These factors generate several constraints for the vaccination process and pose a dilemma between either minimizing the number of vaccination centers and reducing the costs with an improved management, maximizing the coverage or minimizing the travel distances for the population. To address this, an optimization model is put forth as a possible solution to establish optimal location for the vaccination centers.

1.1. Objectives
The objective of this research is to determine the optimal location of vaccination centers in one of the most affected regions of Peru: The Andean region.

2. Literature Review

2.1. Location Optimization Models
Facility location optimization problems can be approached through a discrete facility location model. In this category, coverage models (Set Covering and Maximal Covering), as well as P- Center and P-Median models are the most used models (Owen and Daskin, 1988).

Revelle et al. (1976) provided details of the Set Covering Location model, which consists of the location of facilities in *n* possible nodes in order to minimize location costs while trying to meet their demand. Taking Beasley (1987) as a reference point, a base Set Covering Location model establishes an objective function that intends to minimize facility costs, and restrictions that, on one hand, establish that the demand node is to be covered by at least one facility, and, on the other hand, denote the binary character of the decision variables.

Church and ReVelle (1974) provided a detailed mathematical theory behind the Maximal Covering Location model, which is similar to the Set Covering Location model. However, this intends to maximize coverage of demand by considering a given number of facilities. Taking Beasley (1987) as a reference point, a base Maximal Covering Location model similarly establishes an objective function that intends to minimize the facility costs; however, the restrictions instead establish that the maximum quantity of facilities to locate and condition that demand node has to be covered by one facility that has access to it, while also denoting the binary character of the decision variables.

Hakimi (1964) was the first one to theorize about the P-Center optimization model, which intends to minimize simple distances among n nodes of facilities and m nodes of demand. Taking the proposal by Dantrakul et al. (2014) as a reference, a base P-Center model establishes an objective function that intends to minimize travel costs by using minimum distances, and constraints that define a maximum of operational facilities, ensure the coverage of the demand nodes, establish a relationship between facilities and travels, and denote the binary character of the decision variables.

Likewise with P-Center, Hakimi (1964) was the first one to theorize about the P-Median optimization model, which intends to minimize distances. However, the minimization in P-Median take into consideration a weighting factor. Taking the proposal by Dantrakul et al. (2014) as a reference, a base P-Median model establishes an objective function that intends to minimize travel costs by using minimum distances but weighting them by a factor, and constraints that are the same as the ones in the previous P-Center model.

2.2. Location Optimization Models in the Health Care Sector

As for optimization models used in the health care sector, researchers have built different models according to the objectives intended based on the models described before, or variants and/or combinations thereof.

Gu at el. (2010) created a bi-objective optimization model by prioritizing efficiency and coverage in preventive health care facility location. Özceylan at el. (2017) compared Set Covering, P-Median and M-Center models in a pharmaceutical warehouse optimization. Sharma et al. (2017) developed a temporary facility location model for blood storage in a post-disaster context. Wang and Ma (2018) created a bi-objective optimization model in order to minimize costs and average distances for the demand of nursing home locations, especially considering distance minimization given the characteristics of the target users. Dzator and Dzator (2019) compared the results of applying the Maximal Covering Location Model and the P-Median model for health care locations. Jagtenberg et al. (2021) used location optimization for air ambulance stations focusing on coverage and considering social welfare mathematical functions. Hassan et al. (2021) made a non-linear binary mathematical model based on a Maximal Covering Location Model modified to obtain optimal campaign hospital locations in the COVID-19 pandemic context. Finally, Li et al. (2020) proposed a multi-objective non-linear programming model for vaccination station locations considering distance to stations, operational cost, and work schedule as constraints. These studies are evidence that optimization models can be applied in the sector, especially the latter which shows its applicability, specifically in the vaccination field.

3. Methods

For this research, we consider a more stable post-emergency scenario with a projection for permanent vaccination centers. An inductive experimental method will be used as a start point to determine an applicable model to more general scenarios.

3.1. Location Optimization Model

As a fundamental part of the optimization methodology, a mathematical model will be built. This model, based on the principles of Maximal Covering, Set Covering and P-Median models, will aim to optimize coverage, facility costs and travel distance, concepts that are aligned to the problems presented above.

The mathematical location optimization model will be composed of constants, decision variables, objective function, and constraints.

Constants:

p_j = Rural community population j, expressed in number of inhabitants.

d_{ij} = Distance between the the health care facility i and the rural community j, expressed in kilometers.

r = Coverage radius of the health care facilities, expressed in kilometers.

a = A significantly higher number than b and $c,$ as to establish the model 1° priority

b = A significantly lower number than a but significantly higher than c, as to establish the model 2° priority

c = A significantly lower number than a and $b,$ as to establish the model 3° priority

Decision variables:

X_i = 1 if health care facility *i* is to be assigned as a vaccination center. 0 otherwise.

Y_j = 1 if rural community *j* is to be covered by at least one health care facility. 0 otherwise.

Z_{ij} = 1 if health care facility *i* is to cover rural community *j*. 0 otherwise.

Objective function:

Minimize

$$-a \sum_{j=1}^{m} p_j Y_j + b \sum_{i=1}^{n} X_i + c \sum_{i=1}^{n} \quad \sum_{j=1}^{m} p_j d_{ij} XY_{ij} \quad (1)$$

Constraints:

Subject to:

$$\sum_{i=1}^{n} Z_{ij} \geq \; Y_j;\; \forall\, j = 1, 2, \dots, m \quad (2)$$

$$X_i - Z_{ij} \geq 0, \forall\, i = 1, 2, \dots, n, \forall\, j = 1, 2, \dots, m \quad (3)$$

$$Y_j - Z_{ij} \geq 0, \forall\, i = 1, 2, \dots, n, \forall\, j = 1, 2, \dots, m \quad (4)$$

$$d_{ij} Z_{ij} \leq r, \forall\, i = 1, 2, \dots, n, \forall\, j = 1, 2, \dots, m \quad (5)$$

$$X_i, Y_j, Z_{ij} \,\epsilon\, \{0, 1\}, \forall\, i = 1, 2, \dots, n, \forall\, j = 1, 2, \dots, m \quad (6)$$

For the objective function (1), each sum expresses an individual objective of the model, being prioritized from top to bottom using coefficients a, b, and c.

- The first sum is focused on maximizing coverage as to attain as many rural communities as possible covered by health care facilities, prioritizing those with the largest number of inhabitants.
- The second sum is focused on minimizing costs associated to assigning vaccination centers as to attain as few as possible health care facilities assigned as vaccination centers.
- The third sum is focused on minimizing the travel distance from a rural community to a health care facility as to obtain the lowest total sum of distances, while prioritizing distance minimization for more highly populated rural communities.

As for constraints, they meet the following functions:

- If a rural community is covered, the constraint (2) ensures there is at least one health care facility to cover said rural community.
- If there is a coverage relationship between a given health care facility and any rural community, the constraint (3) ensures said health care facility is assigned as a vaccination center.
- If there is a coverage relationship between any health care facility and a rural community, the constraint (4) ensures said health care facility is assigned as a vaccination center.
- The constraint (5) ensures the health care facility coverage is determined by a distance less or equal to said center coverage radius.
- The constraint (6) defines the binary character of the decision variables.

Finally, alternative scenarios were set for comparative results. A non-optimal comparative scenario was first considered where all health care facilities were to be assigned as vaccination centers. To do this, the model would need to change by adding the following constraint:

$$X_i \geq \; 1;\; \forall\, i = 1, 2, \dots, n \quad (7)$$

The second comparative scenario prioritized reduction of travel distances over reduction of location costs. The initial model was changed by exchanging b and c prioritization coefficients in the objective function sums, resulting in the following function:

Minimize

$$-a \sum_{j=1}^{m} p_j Y_j + c \sum_{i=1}^{n} X_i + b \sum_{i=1}^{n} \quad \sum_{j=1}^{m} p_j d_{ij} XY_{ij}$$

3.2. Sample Determination

The study focused on the Andean region of Peru which includes the regions of Ancash, Apurímac, Arequipa, Ayacucho, Cajamarca, Cusco, Huancavelica, Huánuco, Junín, Pasco, and Puno (INEI, 2014). Out of these regions, only those where Pfizer mRNA vaccine was to be distributed were considered for analysis. In April 2021, the government of Peru determined these regions to be Arequipa, Cusco, and Cajamarca.

The Human Development Index (HDI) will be used to choose from these three alternatives.

Upon the classification by the United Nations Development Programme (2018) this indicator is divided into four levels: low (below 0.550), medium (between 0.550 and 0.699), high (between 0.700 and 0.799) and very high (over 0.800). At present, these regions' indices are as follows: Arequipa 0.6425, Cusco 0.5121 and Cajamarca 0.4251 (United Nations Development Programme, 2019). This research will only use regions with a low HDI. Therefore, Arequipa region is ruled out.

Three criteria were then compared between the regions of Cusco and Cajamarca to define the province for the study:

- Having a low HDI, i.e., below 0.550
- Population being evenly distributed among the districts
- Having at least one secondary health care facility for this will be considered as a possible intermediary management center

La Convención province in Cusco region meets these three selection criteria.

Finally, two criteria were used to define the district for analysis: an HDI between 0.40 and 0.50 (± 0.05 of the province HDI) and a population near the province average of 11,435 inhabitants. Kimbiri district meets these criteria.

4. Data Collection

Upon completion of the first stage, data had to be collected to feed the model. The data included the count, population, and location of rural communities; the count and location of healthcare facilities; the distance between health care facilities and rural communities, and the area of influence of healthcare facilities.

4.1. Rural Communities

Kimbiri district population data was taken from the latest 2017 census published by Instituto Nacional de Estadística e Informática (INEI). Despite having found 76 rural communities in the area of the study, 6 of them were inhabited at the time of the census. Therefore, only 70 rural communities will be considered to run the mathematical model.

Then, rural communities in Kimbiri district were located using an updated 2020 database from Ministerio de Educación (MINEDU) that contained their geographical coordinates. Only the locations for the inhabited rural communites were considered.

With the collected information the following Table 1 was created:

Table 1. Rural Communities

ID	Name	Population	Latitude	Longitude	ID	Name	Population	Latitude	Longitude
1	KIMBIRI	5,913	-12.6200	-73.7890	36	PALMA DE ORO	5	-12.7639	-73.5736
2	VILLA EL SALVADOR	247	-12.5702	-73.7576	37	CORAZON PATA	35	-12.7364	-73.6312
3	CASHIROVENI	94	-12.5692	-73.7320	38	MANITEA BAJA	110	-12.7398	-73.6503
4	POMORENI	36	-12.5905	-73.6933	39	SIRENACHAYOCC	256	-12.7523	-73.6380
5	UBIATO	251	-12.5698	-73.7922	40	UNION VISTA ALEGRE	163	-12.7648	-73.6246
6	CAMONACHARI	138	-12.5783	-73.7937	41	HUAYANAY	106	-12.7755	-73.5567
7	SAMPANTUARI BAJO	16	-12.5874	-73.7904	42	LOBO TAHUANTINSUYO	1,362	-12.7923	-73.6223
8	SAN LUIS	39	-12.5937	-73.7238	43	CHIRUMPIARI	1,122	-12.8079	-73.6036
9	VILLA ESMERALDA	31	-12.6112	-73.7130	44	PALESTINA BAJA	127	-12.8298	-73.5783
10	KIMBIRI ALTA (ROCA)	791	-12.5979	-73.7516	45	PALESTINA ALTA	195	-12.8469	-73.5823
11	SAMPANTUARI ALTA	73	-12.5953	-73.7836	46	LIBERTAD	16	-12.5569	-73.7591
12	VISTA ALEGRE BAJA	138	-12.6067	-73.7503	47	ANARO	98	-12.6105	-73.7874
13	VISTA ALEGRE ALTA	110	-12.6147	-73.7328	48	RANRAPATA	105	-12.6764	-73.6972
14	CAMONIATO	30	-12.6188	-73.7071	49	MAQUETE SANTANIATO	22	-12.7032	-73.6297
15	IVANKIRIARI	272	-12.6396	-73.7000	50	MAQUETE ALTA	117	-12.7079	-73.6522
16	SIBAYLLOHUATO	4	-12.6236	-73.7606	51	SAN MIGUEL	40	-12.7078	-73.6649
17	IRAPITARI	137	-12.6244	-73.7773	52	MASERINE BAJA	4	-12.7750	-73.5957
18	PUERTO RICO	10	-12.6349	-73.7205	53	SAN LUIS ALTO	7	-12.7473	-73.5893
19	KAPIRUSHIATO	64	-12.6551	-73.6775	54	SAN LUIS	15	-12.8066	-73.6135
20	LA LIBERTAD	18	-12.6639	-73.6586	55	SAMPANTUARI NATIVO	379	-12.5997	-73.7728
21	NUEVA CALIFORNIA	124	-12.6803	-73.6590	56	BUENA VISTA	49	-12.6256	-73.7415
22	SOL NACIENTE	43	-12.6631	-73.7019	57	MALVINAS	111	-12.7002	-73.6712
23	SAMANIATO	625	-12.6480	-73.7083	58	KIPASHIARI	16	-12.6566	-73.6502
24	HELARES	256	-12.6736	-73.6798	59	SAN JUAN DE CEVICHARI	36	-12.7261	-73.6545
25	NUEVA ESPERANZA	207	-12.6967	-73.6431	60	CENTRO BELEN	22	-12.7225	-73.6203
26	SANTA FE	91	-12.6959	-73.6613	61	SANTA ANA	42	-12.8359	-73.5672
27	PORVENIR	6	-12.6873	-73.6750	62	NUEVA BETANIA	254	-12.8308	-73.5778
28	LOS ANGELES	179	-12.6794	-73.6975	63	PUGORIARI	14	-12.7762	-73.6218
29	MAPITUNARI	30	-12.6730	-73.6790	64	PANTANAL	55	-12.5834	-73.7918
30	VISTA ALEGRE B	144	-12.7125	-73.6346	65	KITASHIARI	4	-12.6432	-73.6851
31	UNION ROSALES	102	-12.7197	-73.6448	66	PIEDRA LISA	6	-12.7537	-73.6223
32	PROGRESO	220	-12.7051	-73.6698	67	NUEVA LUZ	5	-12.7493	-73.6035
33	MAQUETE SERANTA BAJA	75	-12.7100	-73.6630	68	VILLA FLORES	46	-12.6961	-73.6749
34	MANITEA ALTA	260	-12.7281	-73.6295	69	CERRO DE ORO	18	-12.7344	-73.6156
35	QORICHAYOCC	214	-12.7413	-73.6114	70	ALTO MAYO	12	-12.8165	-73.5665

4.2. Health Care Facilities

First, health care facilities in Kimbiri district were located. Only primary care facilities (categories I-1, I-2, I-3 and I-4) were considered for this study for they are more accessible to the population and their function is focused on preventive health care as it is in the case of vaccination. Data was obtained from an updated 2017 database from Superintendencia Nacional de Salud (SUSALUD). It was found that Kimbiri district had 10 primary care facilities. However, upon a facility location validation process, it was found that Pueblo Libre Health Post was no longer part of Kimbiri district but of Villa Kintiarina. Thus, this facility is ruled out of the study and only 9 health care facilities remain valid.

With the collected information the following Table 2 was created:

Table 2. Health care Facilities

ID	Name	Category	Latitude	Longitude
A	UNION ROSALES	I-1	-12.7196	-73.6444
B	KIMBIRI ALTO	I-1	-12.5992	-73.7553
C	MANITEA ALTA	I-1	-12.7281	-73.6281
D	ANGELES	I-1	-12.6766	-73.6971
E	CHIRUMPIARI	I-2	-12.8059	-73.6043
F	MAPITUNARI	I-2	-12.7054	-73.6694
G	SAMANIATO	I-2	-12.6486	-73.7103
H	LOBO TAHUANTINSUYO	I-3	-12.7947	-73.6209
I	DEL VALLE	I-3	-12.6206	-73.7877

4.3. Distances between Communities and Facilities

After obtaining the coordinates for the 70 rural communities and 9 health care facilities to be considered in the study, distances were estimated using the following formula:

$$d = \frac{R\pi}{180} \cos^{-1}((\operatorname{sen}\alpha \operatorname{sen}\beta) + (\cos\alpha \cos\beta \cos(|\theta - \varphi|)))$$

Where:

R: Earth radius in kilometers (6,371 km).

d: Distance between two geographical points in kilometers.

α, β: Latitudes of the two geographical points in degrees.

θ, φ: Longitudes of the two geographical points in degrees.

This formula was used to determine 630 distances between health care facilities and rural communities.

4.4. Area of Influence for Health Care Facilities

A coverage radius in kilometers as described by Albrieu and Pastor (2012) was used to determine the health care centers area of influence. This criterion considers health care centers as travel generating poles (PGVs), i.e., points that attract or generate a great travel demand.

Upon this concept, the area of influence is divided into three categories: primary area, secondary area, and tertiary area with different radii around this PGV. Each category has a different radius depending on the area of the facility. The primary area ranges from 4 to 8 km, the secondary area ranges from 8 to 11 km, and the tertiary area ranges from 11 to 24 km (Albrieu and Pastor, 2012).

Since 81,8 % of the population in the Andean region go to their health care center on foot, the coverage radius for this study was only the primary area of influence so as to cover the demand with a near health care center. Additionally, the lower limit of the primary area was considered since I-4 health care facilities – the highest category of the first level – have a minimum area of 350 m^2 (Ministerio de Salud del Perú, 2015) and according to Kneib et al. (2010), it is considered a micro pole or center.

5. Results and Discussion

In order to input the data into the model, it had to be transferred into a solver program. For that purpose, the software Lingo 19.0 was used. The optimization model and the data sources were transcribed into its own scripting language, as shown in Figure 1.

```
MODEL:

SETS:
ESTABLECIMIENTOS/1..9/:X;
CENTROS_POBLACION/1..70/:POBLACION,Y;
EXC(ESTABLECIMIENTOS,CENTROS_POBLACION):DISTANCIA,Z;
ENDSETS

DATA:
POBLACION = @OLE('C:\Users\sebas\OneDrive\Documentos\Cosas Sebastian\SEBASTIAN ULIMA\ARTÍCULO CIENTÍFICO\Artículo Científico - Data Lingo.xlsx','POBLACION');
DISTANCIA = @OLE('C:\Users\sebas\OneDrive\Documentos\Cosas Sebastian\SEBASTIAN ULIMA\ARTÍCULO CIENTÍFICO\Artículo Científico - Data Lingo.xlsx','DISTANCIA');
a = 100000;
b = 1000;
c = 0.001;
RADIO_COBERTURA = 4;
@OLE('C:\Users\sebas\OneDrive\Documentos\Cosas Sebastian\SEBASTIAN ULIMA\ARTÍCULO CIENTÍFICO\Artículo Científico - Data Lingo.xlsx','X') = X;
@OLE('C:\Users\sebas\OneDrive\Documentos\Cosas Sebastian\SEBASTIAN ULIMA\ARTÍCULO CIENTÍFICO\Artículo Científico - Data Lingo.xlsx','Y') = Y;
@OLE('C:\Users\sebas\OneDrive\Documentos\Cosas Sebastian\SEBASTIAN ULIMA\ARTÍCULO CIENTÍFICO\Artículo Científico - Data Lingo.xlsx','XY') = Z;
ENDDATA

MIN = -a*@SUM(CENTROS_POBLACION(J):Y(J)*POBLACION(J)) + b*@SUM(ESTABLECIMIENTOS(I):X(I)) + c*@SUM(EXC(I,J):DISTANCIA(I,J)*POBLACION(J)*Z(I,J));

@FOR(ESTABLECIMIENTOS(I):      [BIN_ESTABLECIMIENTOS]  @BIN(X(I)));
@FOR(CENTROS_POBLACION(J):     [BIN_CENTROS_POBLACION] @BIN(Y(J)));
@FOR(EXC(I,J):                 [BIN_EXC]               @BIN(Z(I,J)));
@FOR(CENTROS_POBLACION(J):     [REST_APERTURA_CP]      @SUM(ESTABLECIMIENTOS(I):Z(I,J)) >= Y(J));
@FOR(EXC(I,J):                 [REST_COBERTURA_EST]    X(I) - Z(I,J) >= 0);
@FOR(EXC(I,J):                 [REST_COBERTURA_CP]     Y(J) - Z(I,J) >= 0);
@FOR(EXC(I,J):                 [REST_RADIO_INFLUENCIA] Z(I,J)*DISTANCIA(I,J) < RADIO_COBERTURA);

END
```

Figure 1. Original model in Lingo code

After executing the script, Lingo recognized the model as a Pure Integer Linear Program and used a Branch-and-Bound algorithm to determine an optimal global solution. (Figure 2)

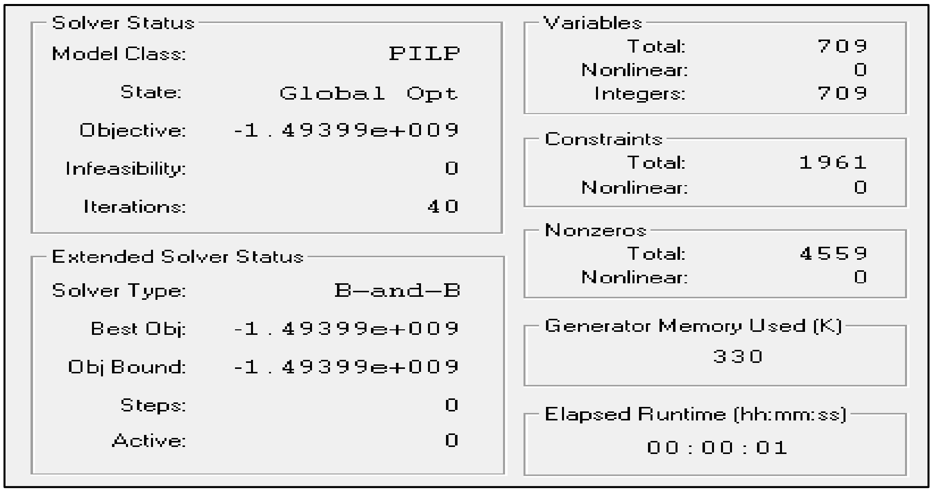

Figure 2. Lingo Solver Output

The Tables below show the relationship between the assigend health care facilities and the covered rural communities, as well as information regarding the pupulation that is being covered and the weighted distance that resulted from the assignments. The original model optimal solution is shown in Table 3, and those of the alternative models are summarized in Tables 4 and 5.

Table 3. Results from Base Scenario

HCF	RC	Population covered	% of population covered	Distance (Km) * Population
A	-	0	0.00%	0.00
B	2, 8, 10, 12, 13, 16, 55, 56	1,757	11.01%	2,636.21
C	30, 31, 34, 35, 37, 38, 39, 49, 60, 66, 67, 69	1,194	7.48%	2,236.37
D	-	0	0.00%	0.00
E	43, 44, 54, 62	1,518	9.51%	1,781.97
F	21, 24, 25, 26, 27, 29, 32, 33, 50, 51, 57, 59, 68	1,359	8.51%	2,740.84
G	14, 15, 18, 19, 22, 23, 28, 48, 65	1,332	8.34%	2,013.73
H	40, 42, 52, 63	1,543	9.67%	1,004.43
I	1, 7, 11, 17, 47	6,237	39.07%	1,469.39

*HCF: Health Care Facilities. RC: Rural communities

Table 4. Results from Alternative Scenario 1

HCF	RC	Population covered	% of population covered	Distance (Km) * Population
A	25, 30, 31, 38, 49, 50, 59	738	4.62%	1,263.52
B	2, 8, 10, 12, 13, 16, 55, 56	1,757	11.01%	2,636.21
C	34, 35, 37, 39, 60, 66, 67, 69	816	5.11%	1,397.13
D	19, 22, 24, 28, 29, 48	677	4.24%	879.90
E	43, 44, 54, 62	1,518	9.51%	1,781.97
F	21, 26, 27, 32, 33, 51, 57, 68	713	4.47%	731.96
G	14, 15, 18, 23, 65	941	5.90%	682.55
H	40, 42, 52, 63	1,543	9.67%	1,004.43
I	1, 7, 11, 17, 47	6,237	39.07%	1,469.39

*HCF: Health Care Facilities. RC: Rural communities

Table 5. Results from Alternative Scenario 2

HCF	RC	Population covered	% of population covered	Distance (Km) * Population
A	25, 30, 31, 38, 49, 50, 59	738	4.62%	1,263.52
B	2, 8, 10, 12, 13, 16, 55, 56	1,757	11.01%	2,636.21
C	34, 35, 37, 39, 60, 66, 67, 69	816	5.11%	1,397.13
D	19, 22, 24, 28, 29, 48	677	4.24%	879.90
E	43, 44, 54, 62	1,518	9.51%	1,781.97
F	21, 26, 27, 32, 33, 51, 57, 68	713	4.47%	731.96
G	14, 15, 18, 23, 65	941	5.90%	682.55
H	40, 42, 52, 63	1,543	9.67%	1,004.43
I	1, 7, 11, 17, 47	6,237	39.07%	1,469.39

*HCF: Health Care Facilities. RC: Rural communities

Additionally, the results were expressed in a visual way by locating the coordinates from Table 1 and Table 2 in Google Maps, and using the results from Table 3, Table 4 and Table 5 to represent the asignments and the existing relationships according to each model. In the maps below, the black dotted line represents the limits of the Kimbiri district, the location markers represent the health care facilities and the dots represent the rural comunnities. For the healh care facilities, the green markers represent those that, according to the model, should be assigned as a vaccination centers, whereas the red ones represent those that shouldn't. Similarly, for the rural comunnities, the blue dots represent those that, according to the model, would be covered by a nearby vaccination center, whereas the red ones represent those that wouldn't be. Finally, the lines that connect the green markers with the blue dots represent the relationship where a health care facility would cover a rural community.

It is worth mentioning that, since the results for both alternative scenarios are the same, they were represented in the same map.

(Figure 3)

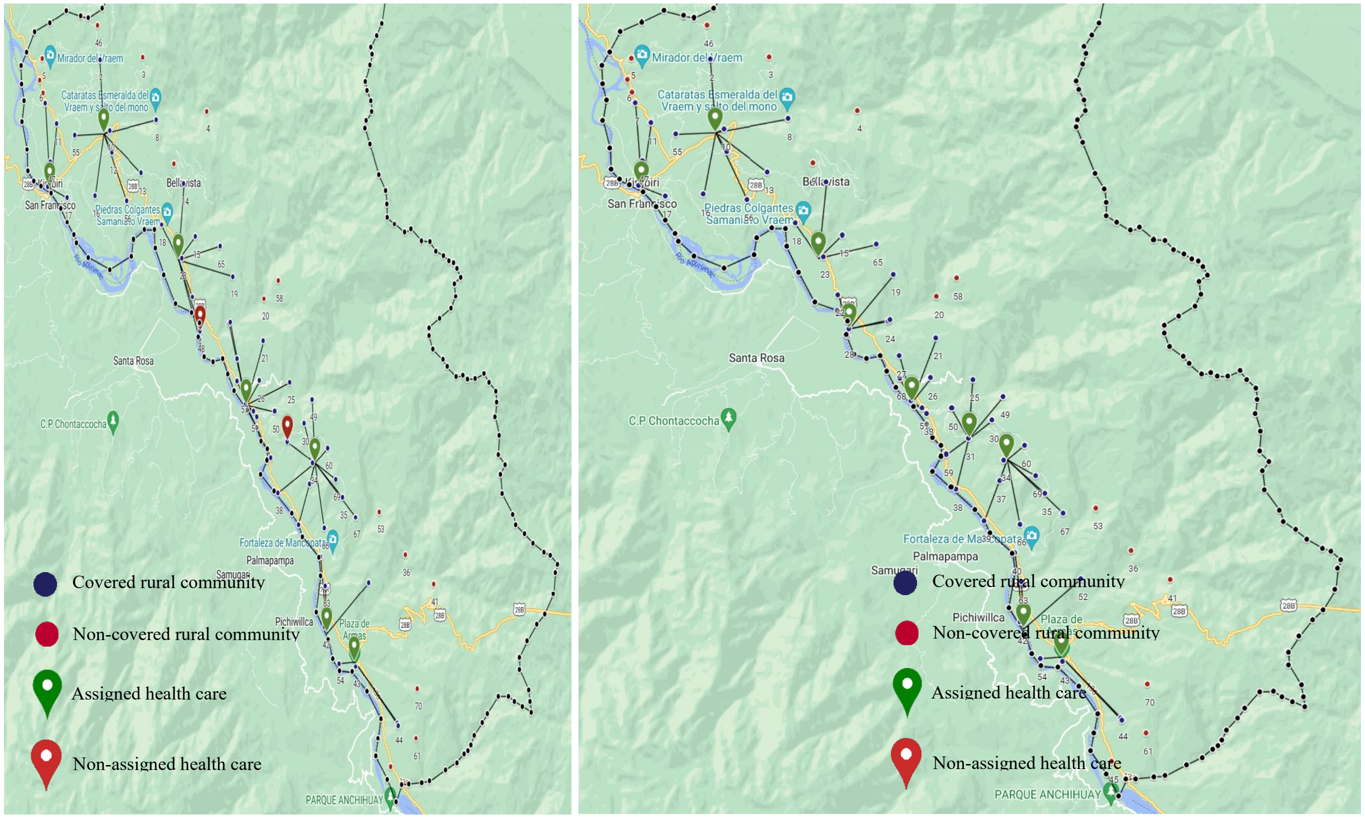

Figure 3. Assignments made upon Base Scenario (Left) and Alternative Scenarios (Right)

Furthermore, three performance indicators were proposed and assessed for model results analysis: (Table 6)

- Coverage: represents the population covered by a health care facility.
- Resources used: represents the number of health care facilities assigned as vaccination centers for, as mentioned above, resources used are proportional to the number of vaccination centers available.
- Average travel distance: represents the average individual travel distance between the health care facility and the rural community, weighted by the population of each community.

Table 6. Performance Indicators

Scenario	Coverage	Resources Used	Average Travel Distance
Base	93.60%	77.78%	0.9292
Alternative 1	93.60%	100.00%	0.7930
Alternative 2	93.60%	100.00%	0.7930

Upon comparison of the optimization results from the base scenario and from the other scenarios, it can be noted that when alternating location cost and travel distance priorities, the resources used for location should increase in 28.57% as to reduce the average travel distance in 14.66%. However, the current average travel distance is less than 1 km, significantly less than the maximum travel distance established (4 km). Therefore, the decrease in average travel distance is less substantial when compared to the increase in resources used.

Likewise, when comparing the results from the other scenarios, it can be observed that both alternative scenario 2 which prioritizes the decrease of the travel distance over the decrease of location costs, and alternative scenario 1 which assumes all health care facilities are to be assigned as vaccination centers, have the same results and indicators. This would indicate that the health care facility distribution from the base scenario provides an optimal distribution.

6. Conclusion

The mathematical model for location optimization successfully defined an optimal location for vaccination centers in the most adverse regions of Peru, and it was attained by using Lingo software with reliable results. Additionally, after comparing the results of the main optimization scenario with alternative one, it can be concluded that the location distribution is optimal. Finally, due to the nature of the method and data used in this optimization, the model can be used to optimize immunization processes for different vaccines or for other medications, and it can be applied in other developing countries.

References

Albrieu, M. L., y Pastor, G. Área de Influencia de Hospitales en la Ciudad de Córdoba. Available: http://redpgv.coppe.ufrj.br/index.php/es/produccion/articulos-cientificos/2012-1/702-rea-de-influencia-de-hospitales-cordoba-panam-2012/file, Accessed Day: June 10, 2021.

Baray, J., y Cliquet, G. Optimizing locations through a maximum covering/p-median hierarchical model: Maternity hospitals in France. *Journal of Business Research*, vol. 66, no. 1, pp. 127-132, 2013.

Beasley, J. E. An algorithm for set covering problem. *European Journal of Operational Research*, vol. 31, no. 1, pp. 85–93, 1987.

Burgos, R., Badowski, M., Drwiega, E., Ghassemi, S., Griffith, N., Herald, F., Johnson, M., Smith, R. O., y Michienzi, S. M. The race to a COVID-19 vaccine: opportunities and challenges in development and distribution. *Drugs in Context*, *10*, 2020.

Church, R., y ReVelle, C. The Maximal Covering Location Problem. *Papers in Regional Science*, vol. *32,* no.1, 1974.

Comité Regional De La Oms Para Las Américas. Estrategia Para El Acceso Universal A La Salud Y La Cobertura Universal De Salud. Available: https://www.paho.org/hq/dmdocuments/2014/CD53-R14-s.pdf, Accessed Day: April 18, 2021.

Dantrakul, S., Likasiri, C., y Pongvuthithum, R. Applied p-median and p-center algorithms for facility location problems. *Expert Systems with Applications*, vol. 41, no. 8, pp. 3596-3604. (2014).

Departamento de Inmunizaciones y la Subsecretaría de Salud Pública. Lineamientos Técnicos Operativos Vacunación Contra Sars-Cov2 2021. Available: https://www.minsal.cl/wp-content/uploads/2020/12/RE-Nº-1138-Lineamientos-SARS-CoV-2.pdf: Accessed Day: April 18, 2021.

Diario Gestión. Coronavirus en Perú: ¿A qué regiones se distribuirán las vacunas de Astrazeneca y desde cuándo? Available: https://gestion.pe/peru/coronavirus-en-peru-en-que-regiones-se-distribuiran-vacunas-contra-el-covid-19-de-astrazeneca-y-desde-cuando-ayacucho-tumbes-huanuco-nndc-noticia/, Accessed Day: April 23, 2021.

Dirección General de Personal de la Salud del Ministerio de Salud del Perú. Compendio Estadístico: Información de Recursos Humanos del Sector Salud - Perú 2013 – 2018. Available: http://bvs.minsa.gob.pe/local/MINSA/10896.pdf, Accessed Day: April 18, 2021.

Duijzer, L. E., Van Jaarsveld, W., y Dekker, R. Literature review: The vaccine supply chain. *European Journal of Operational Research*, vol. 268, no. 1, pp. 174-192, 2018.

Dzator, M., y Dzator, J. Optimization models to locate health care facilities. *23rd International Congress on Modelling and Simulation*, Canberra, ACT, Australia, December 1–6, 2019, pp. 96-101.

Gu, W., Wang, X., y McGregor, E. Optimization of preventive health care facility locations. *International Journal of Health Geographics*, vol. 9, no. 1, article 17, 2010.

Hakimi, S. Optimum Locations of Switching Centers and the Absolute Centers and Medians of a Graph. *Operations Research*, vol. 12, no. 3, pp. 450-459, 1964.

Hassan, S. A., Alnowibet, K., Agrawal, P., y Mohamed, A. W. Optimum Location of Field Hospitals for COVID-19: A Nonlinear Binary Metaheuristic Algorithm. *Computers, Materials y Continua*, vol. 68, no. 1, pp. 1183–1202, 2021.

Instituto Nacional de Estadística e Informática. Estado de la Población Peruana 2014. Available: https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1157/libro.pdf, Accessed Day: June 08, 2021.

Instituto Nacional de Estadística e Informática. Directorio Nacional de Centros Poblados, 2017. Available: https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1541/index.htm, Accessed Day: June 08, 2021.

Instituto Nacional de Estadística e Informática. (2018). Infraestructura Urbana y Rural, Acceso a Servicios Sociales básicos en Comunidades Rurales, 2018. Available: https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1520/cap03.pdf, Accessed Day: June 03, 2021.

Jagtenberg, C., Vollebergh, M., Uleberg, O., y Røislien, J. Introducing fairness in Norwegian air ambulance base location planning. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*, vol. *29, no.* 1, article 50, 2021.

Joint United Nations Programme on HIV/AIDS. Rich nations vaccinating one person every second while majority of the poorest nations are yet to give a single dose. Available: https://www.unaids.org/en/resources/presscentre/featurestories/2021/march/20210310_covid19-vaccines, Accessed Day: April 26, 2021.

Kneib, E., Lemos, D., Andrade, E., & Palhares, M. Cadernos Polos Geradores de Viagens Orientados à Qualidade de Vida e Ambiental. Available: http://redpgv.coppe.ufrj.br/index.php/pt-BR/cadernos/modulo-i/caracterizacaoo-dos-pgvs?download=88:caderno-1-preliminar, Accessed Day: June 10, 2021.

Li, X., Pan, Y., Jiang, S., Huang, Q., Chen, Z., Zhang, M., y Zhang, Z. Locate vaccination stations considering travel distance, operational cost, and work schedule. *Omega*, vol. *101*, article 102236, 2020.

Ministerio de Educación del Perú. Descarga de información espacial del MED. Available: http://sigmed.minedu.gob.pe/descargas/, Accessed Day: June 14, 2021.

Ministerio de Salud del Perú. Norma Técnica de Salud "Infraestructura y Equipamiento de los Establecimientos de Salud del Primer Nivel de Atención". Available: http://bvs.minsa.gob.pe/local/minsa/3366.pdf, Accessed: April 10, 2021.

Ministerio de Salud del Perú. Diagnóstico De Brechas De Infraestructura Y Equipamiento Del Sector Salud. Available: https://www.minsa.gob.pe/Recursos/OTRANS/08Proyectos/2021/DIAGNOSTICO-DE-BRECHAS.pdf, Accessed Day: April 17, 2021.

Ministerio de Transporte y Comunicaciones del Perú. Red Vial Existente del Sistema Nacional de Carreteras, según Departamento: 2010-2018. Available: http://portal.mtc.gob.pe/estadisticas/transportes.html, Accessed Day: April 23, 2021.

Owen, S. H., y Daskin, M. S. Strategic facility location: A review. *European Journal of Operational Research*, vol. 111, no. 3, pp. 423-447, 1998.

Özceylan, E., Uslu, A., Erbaş, M., Çetinkaya, C., İşleyen, S. K. Optimizing the location-allocation problem of pharmacy warehouses: A case study in Gaziantep. *International Journal of Optimization and Control: Theories & Applications (IJOCTA)*, vol. 7, no. 1, pp. 117–129, 2017.

Revelle, C., Toregas, C., y Falkson, L. Applications of the Location Set-covering Problem. *Geographical Analysis*, vol. 8, no. 1, pp. 65-76, 1976.

Sharma, B., Ramkumar, M., Subramanian, N., y Malhotra, B. Dynamic temporary blood facility location-allocation during and post-disaster periods. *Applications of OR in Disaster Relief Operations*, vol. 283, no. 1, pp. 705-736, 2017.

Sociedad de Comercio Exterior del Perú. Informe de Calidad del Gasto Público en Salud 2019. Available: https://www.comexperu.org.pe/upload/articles/reportes/informe-calidad-001.pdf, Accessed Day: April 04, 2021.

Superintendencia Nacional de Salud. Listado de Instituciones Prestadoras de Salud. Available: https://www.datosabiertos.gob.pe/dataset/minsa-ipress/resource/7cf96151-5ddf-4281-90ba-b2b0407447ab#{}, Accessed Day: June 02, 2021.

United Nations. World's Most Vulnerable Countries Lack the Capacity to Respond to a Global Pandemic Credit: MFD/Elyas Alwazir. Available: https://www.un.org/ohrlls/news/world's-most-vulnerable-countries-lack-capacity-respond-global-pandemic-credit-mfdelyas-alwazir, Accessed Day: April 19, 2021.

United Nations Development Programme. Índices e indicadores de desarrollo humano. Available: http://hdr.undp.org/sites/default/files/2018_human_development_statistical_update_es.pdf, Accessed Day: May 20. 2021.

United Nations Development Programme. El reto de la igualdad: Una lectura de las dinámicas territoriales en el Perú. Available: https://www1.undp.org/content/dam/peru/docs/Publicaciones%20pobreza/PNUD%20Peru%20-%20El%20Reto%20de%20la%20Igualdad.pdf, Accessed Day: May 20, 2021.

Wang, S., Ma, S. Efficient methods for a bi-objective nursing home location and allocation problem: A case study. *Applied Soft Computing*, vol. 65, no. 1, pp. 280–291, 2018.

World Health Organization. Health Workforce Requirements For Universal Health Coverage And The Sustainable Development Goals. Available: https://apps.who.int/iris/bitstream/handle/10665/250330/9789241511407-?sequence=1, Accessed Day: April 14, 2021.

Biography

Sebastian Cuya studied at the University of Lima, where he obtained his bachelor's degree in Industrial Engineering and graduated as Valedictorian of his class. He has worked in one of the world's most important audit firms, in charge of the transformation, modelling and analysis of financial data in order to ensure compliance with regulations of global customers, including fortune 500 companies. In addition, he has been working in one of the world's most important consulting firms, participating in projects oriented towards the planning, design and implementation of solutions in the fields of data analytics and business intelligence for world renowned companies.

Mariela Lima studied at the University of Lima, where she obtained her bachelor's degree in Industrial Engineering. She has worked in one of the world's most important information and technology companies, participating in implementing and deploying AP S/4 HANA ERP solutions for different regional companies focused on the logistics module. In addition, she has been working in one of the most important banks in Peru managing a $10MM portfolio of more than 60 clients, conducting financial analysis of the needs and requirements of the portfolio, and monitoring the annual budget identifying deviations, reductions, and growth.

Rosa Patricia Larios-Francia Ph.D. candidate in Strategic Management with mention in Business Management and Sustainability from the Consortium of Universities, Master in Industrial Engineering from the Ricardo Palma University and Industrial Engineer from the University of Lima. With specialization in innovation by the International High Specialization Program in Innovation Management of ESAN and La Salle Ramon Llull University of Spain. Professor and Researcher at the University of Lima in the areas of innovation, MSME management, cluster, Biodiversity, sustainability, circular economy, humanitarian logistics, processes in the fashion textile industry and handicrafts. She has served as director of the Center for Textile Innovation. Author of scientific articles and book on innovation, sustainability and MSME management. With more than twenty years of experience in executive positions in the manufacturing sector, specialist in the areas of innovation, design, product development, marketing and operations. Member of the Technical Committees ISO/TMBG/SAG_ESG "Strategic Advisory Group on Environmental, social, governance (ESG) ecosystem"; ISO/TC 133 "Clothing sizing systems-size designation, size measurement methods and digital fittings"; ISO/TC 279/WG1 Innovation Management system" and of the STTF ISO TC 279.