Regionalization of Primary Health Care Units with Multi-Institutional Collaboration[a]

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May 2020

[a]Preprint PISIS-RR20-01, Graduate Program in Systems Engineering, UANL, San Nicolás de los Garza, México, May 2020

Abstract

In this paper, the problem of locating and upgrading primary healthcare units within a multi-institutional public system is addressed. The problem is motivated by a real-world application in the Mexican Healthcare System. Decisions also involve allocating customer demand to those facilities with the goal of minimizing the total travel distance in a capacitated facility location problem. The capacity is measured in units named basic kernels composed by a group of medical staff for outpatient services. A mixed-integer linear programming model is proposed. A computational study based on a case study in the State of Mexico is carried out. Test instances are successfully solved by branch and bound. The distribution of patient-to-healthcare unit distances and the variation of the capacity utilization rate of health care units are analyzed. Among the results, we found that balancing the utilization rates between healthcare units has a negative impact on the total travel distance. The capacity of a kernel can be modified to balance the utilization rates or when the demand is greater than the capacity in the system. The results presented in this paper open the opportunity of using OR tools in the planning of healthcare resources in developing countries to face the challenges of the next decade in health matters.

Keywords: Healthcare planning; Public healthcare; Facility location; Integer programming.

1 Introduction

The planning of public resources implies analyzing a considerable quantity of information to make the best decisions for the community. In developing countries, some decisions are not optimized because the decision-makers do not have access to technology, data and adequate tools for this purpose. In this sense, this paper tries to show the application of Operation Research (OR) tools to improve the access and quality of the public primary healthcare services through the planning of resources.

In Mexico, for instance, according to INEGI, the Mexican Institute of Statistics, Geography, and Informatics, the three main causes of death in 2015 were ischemic heart disease, chronic kidney disease, and diabetes mellitus [18]. These problems could be controlled or avoided by prompt preventive healthcare attention. The lack of access and the deficient quality attention prevent the population from check-up or follow-up their health. High quality in the provision of healthcare services can help the government tackle some of these problems [45].

The State of Mexico was the most populated in Mexico with more than 15 million inhabitants, being 1.7 times more inhabited than the second place in 2010 [17], and this trend continues in 2015 [18]. This state has two types of contrasting regions. One of them is the urban area nearest to Mexico City with a high population density presenting remarkably high rates of poverty with regular access to healthcare services but with a current overload of demand due to the high population density. On the other hand, the rural areas present elevated levels of poverty but with separate healthcare units (HCUs) with low rates of demand.

In Mexico, the healthcare system is composed of many institutions that supply services to different segments of the population. The three main public institutions are the Ministry of Health, the Mexican Social Security Institute (IMSS, from *Instituto Mexicano de Seguro Social*), and the Institute of Security and Social Services for State Workers (ISSSTE, from *Instituto de Seguridad Social para los Trabajadores del Estado*). In Figure 1, the institutions that offer healthcare services in the State of Mexico are shown. The Institute of Health for Well-being (INSABI, from *Instituto de Salud para el Bienestar*) is an institution created this year (2020) to provide the services for people without insurance in all the country. This institution uses the resources of the Institute of Health in the State of Mexico (ISEM, from *Instituto de Salud del Estado de México*) and the IMSS-Bienestar (the institution that belongs to IMSS created to attend extreme poverty regions).

The ISEM, in collaboration with INSABI, controls the resources about 75% of all public HCUs in the State of Mexico. Formerly, each inhabitant was assigned to a unique HCU with "public insurance" (currently extinct). The assignment was based on the proximity between the localities and the location of HCUs. This allocation is named as "regionalization" because this term has been used by healthcare institutions when referring to this type of issue [16], and it is likely that

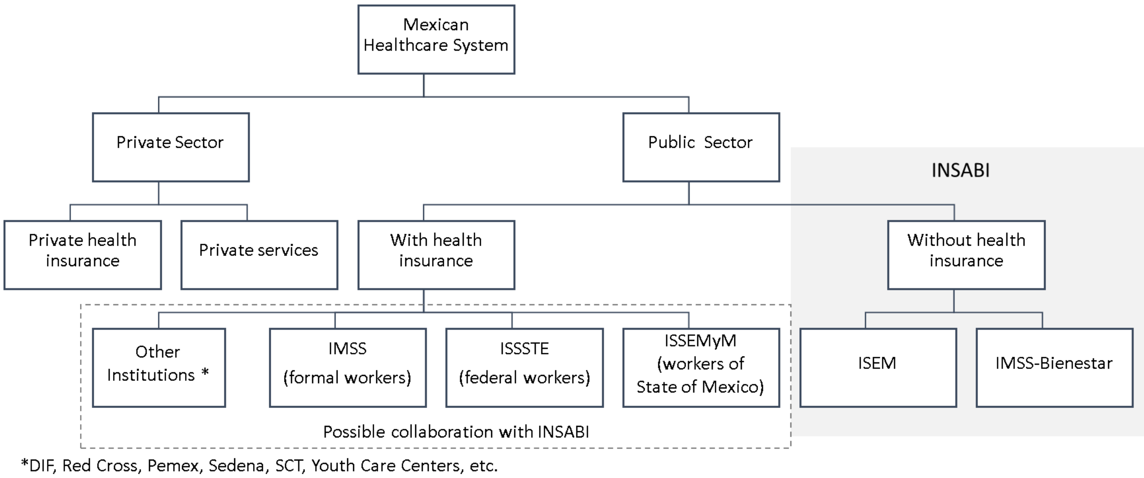

Figure 1: The composition of the healthcare system in the State of Mexico.

regionalization continues being used in the following years. Other institutions such as the IMSS, the ISSSTE, and ISSEMyM have fewer HCUs concentrated in urban areas of some municipalities. Therefore, insured people have fewer problems finding which clinic they are affiliated to.

We summarized some detected problems of the current regionalization of primary healthcare services of the ISEM in recent years.

- The capacity and the allocated demand are not well balanced in some HCUs. In some cases, HCUs are crowded while others are empty.
- The allocation is restricted to municipal limits, even though, this local entity does not provide the services. Removing those limitations will increase the options to the population since the nearest HCU is not necessarily in the same municipality in some cases.
- There is no evident collaboration between institutions to improve the coverage of primary healthcare services.

The regionalization must consider the closeness with localities and the capacity, eliminating the municipality limits. Although the population is not compelled to follow the regionalization, it has benefits for them and the institutions because they have a medical history, and the institutions can have better planning of resources.

In the ISEM, the capacity of the primary HCUs is defined by the number of “kernels”. A kernel is compound by a doctor, two nurses, and one technical staff, but this could change depending on the disposition of the human resources in the region. Sometimes a medical intern or only one nurse are assigned to HCUs. The management of services and staff in the ISEM is conformed by sanitary jurisdictions, each of them is integrated by several municipalities.

One of the contributions of this in this paper is the integration of the other public healthcare institutions, to consider multiples municipalities into the analysis (e.g., by jurisdictions), the standardization of capacity through the use of the kernel as basic unit for all institutions, and the evaluation of additional capacity or location of new HCU.

To this purpose, an integer programming model to define the regionalization of primary healthcare services applied to Mexico Healthcare System is presented. This problem considers the minimization of the total distance traveled (TDT) by the population, with the objective of improving access to healthcare. The usage of the capacity of HCUs is constrained to balance the workload. To illustrate the usefulness of the proposed model, a case study taken from the State of Mexico, one of the most complicated states of Mexico due to the variety of characteristics of the population and geographical regions, is presented.

Table 1: The population characteristics in the State of Mexico by jurisdictions.

Jurisdiction	Mun.	Area (km^2)	Population (1 000 inh.)	Localities	Density (inh/km^2)	Extreme Poverty (%)	Lack of HC Services(%)	Lack of HC Insurance (%)
Group 1	**95**	**18,639**	**5,987**	**4,422**	**321**	**53.8**	**32.3**	**44.05**
Ixtlahuaca	6	1,982	551	499	278	8	1.5	4.76
Jilotepec	7	2,065	255	306	124	2.4	0.6	2.05
Tejupilco	6	3,476	205	894	59	3.9	0.3	1.61
Valle de Bravo	9	2,003	306	430	153	5.2	0.8	2.67
Atlacomulco	4	1,233	268	281	217	3.5	0.9	2.17
Tenancingo	12	2,778	408	568	147	5	1.3	3.5
Tenango del Valle	13	803	392	220	488	2.6	2.2	3.02
Teotihuacán	7	908	347	231	382	2.1	1.9	2.72
Xonacatlán	7	888	796	296	896	4.3	3.6	5.06
Amecameca	14	1,504	1,498	455	996	12.9	12.5	10.91
Zumpango	9	999	961	242	962	3.8	6.8	5.57
Group 2	**31**	**3,747**	**10,200**	**840**	**2,722**	**46.2**	**67.7**	**55.95**
Atizapán	3	403	945	70	2,348	2.9	6.1	4.83
Cuautitlán	8	540	1,611	137	2,982	5	10.6	7.28
Ecatepec	2	195	1,962	9	10,048	8.4	15.2	10.37
Naucalpan	2	276	863	79	3,124	3	5.4	4.17
Nezahualcóyotl	2	100	1,334	25	13,323	5.8	9.3	7.83
Texcoco	9	842	1,318	209	1,566	10.3	10.5	9.96
Tlalnepantla	1	77	701	5	9,080	2	3.9	3.1
Toluca	4	1,314	1,467	306	1,116	8.8	6.6	8.41
Total	**125**	**22,388**	**16,188**	**5,262**	**723**	**100**	**100**	**100**

Sources:[17; 18], CONEVAL:https://www.coneval.org.mx

In Table 1, all the characteristics of the population in the State of Mexico, segmented by jurisdictions, are presented. The number of municipalities, the territorial surface, the number of inhabitants, the number of localities, and the population density by sanitary jurisdictions are shown in columns 2 to 5. Some indicators obtained from CONEVAL (*https://www.coneval.org.mx/*) are shown in the last three columns: the percentage of the population that lives in extreme poverty, the percentage of the population with lack of healthcare services, and the percentage of the population with lack of healthcare insurance. The jurisdictions are divided into two groups. Group 1 represents the rural regions with lower population density compared with the ones of group 2. The case study is based on data from group 1 since it represents 75% of municipalities and 85% of the land area, with 53% of people that live in extreme poverty. For group 2, detailed data is not available to apply the model yet, but this work is also extendable to this type of region.

The remainder of the paper is organized as follows. A discussion of relevant literature is given in Section 2. Section 3 describes the problem and presents the proposed integer programming model. The application of the model in a case study in the State of Mexico is presented in Section 4. This includes a sensitivity analysis on several key parameters, such as HCU capacity. Finally, concluding remarks and future research directions are shown in Section 5.

2 Literature Review

Facility location models have been widely used for addressing location decisions in many areas such as logistics, supply chain management, operation management, emergency services, public services, and healthcare planning, for naming a few. Excellent surveys on facility location are presented by ReVelle and Eiselt [35]; Klose and Drexl [20]; ReVelle et al. [36]; Farahani and Hekmatfar [9]; Melo et al. [23]. In terms of healthcare facility location models, a survey in the context of the public sector is presented by Daskin and Murray [7], and a more recent survey is presented in Ahmadi-Javid et al. [2]. In particular, this last review of primary healthcare facilities is revisited and extended in Appendix A.

We focus our discussion on some relevant contributions in the field of facility location in healthcare that have been recently studied. In Shariff et al. [38], a maximal covering location problem with limited capacity was proposed to study the healthcare facilities of one of the districts in Malaysia. Given the intractability of the integer programming model, the authors developed a genetic algorithm that was able to solve an instance of 809 nodes. In Syam and Côté [43] was proposed an integer programming model to locate specialized healthcare services for US veterans in a network of facilities, minimizing the total cost of service incorporating retention rates based on the distance traveled, and multiple levels of patient acuity that are used to define targets. Another model applied to locate a specialized service (sleep apnea service) for veterans was proposed by Benneyan et al. [4]. A multi-period model was proposed minimizing the total installation and operation costs of the service, considering the number of sleep beds required in each facility each period.

In Kim and Kim [19], a healthcare facility location problem with two types of patients (low-income and high-income) and two types of facilities (public and private) was proposed. The objective was to maximize the number of patients allocated to the healthcare facilities constrained to a budget for the establishment of new public facilities. The problem was applied in Korea using a heuristic algorithm based on Lagrangian relaxation and subgradient optimization. Two mixed-integer linear programming models were developed by Mestre et al. [27]. The first model considers location as the first-stage decision and the second considers location, and allocation as the first-stage decision. Uncertainty was associated with demand. The authors presented a case study based on the Portuguese National Health Service.

In Zhang et al. [46], a multi-objective location-allocation model for healthcare facilities was applied in a case study in Hong Kong. The objectives were to maximize the accessibility of the population, to minimize the inequity of accessibility, to minimize the uncovered population, and to minimize the cost of building new healthcare facilities. This multi-objective problem was addressed by employing a genetic algorithm. The capacity level was a decision variable, just as we do in this paper. In Taymaz et al. [44], a stochastic healthcare facility location problem for mobile workers that incorporates multiple diseases and multiple services was proposed. A risk-averse approach was integrated into the decision making process associated with the lack of coverage based on the location of clinics.

Previous works that dealt with location-allocation of resources in public healthcare with inter-institutional collaboration were presented by Mendoza-Gómez et al. [25]; Mendoza-Gómez et al. [24]. Those works focused on the planning of specialized healthcare services in a network of public hospitals in Mexico. The authors presented an integer programming model and develop a meta-heuristic based on the iterated greedy algorithm with a variable neighborhood search.

We provide an integer programming model for finding an optimal solution to a real-world planning problem that currently faces a tremendous challenge due to the actual conditions of healthcare in Mexico. The proposed model incorporates novel features, such as the multiple institution scheme in the public sector and the use of a basic unit to measure the capacity of the facilities. These are particular characteristics of the Mexican Healthcare System that are included. We present a case study in Mexico as a new open resource for the application of facility healthcare location theory. This tool for decision-makers can be straightforwardly implemented with available data and off-the-shelve integer programming solvers.

3 Problem Description

The problem is the allocation of demand to HCUs of multiple institutions and the location of additional capacity to minimize the total distance traveled by people from the demand points to the location of the HCUs. In this scheme, institutions have their demand and their HCUs, but the capacity can be shared among them to enlarge the global capacity of the system. The capacity of an HCU is determined by its number of kernels. This basic unit of capacity determines the amount of the population that can be covered by a medical work team (doctor, nurses, and technicians).

3.1 Formulation

This problem was formulated as a capacitated location problem with additional side constraints to account for the particular requirements of the problem. The notation, parameters, and variables used in the problem formulation are the following:

Indices and sets:

$i \in N$	Set of demand locations.
$j \in M$	Set of locations for HCUs (actual and potential locations).
$k, l \in K$	Set of institutions.

Parameters:

C	Maximum number of people covered by a kernel.
d_{ij}	Distance from location i to location j.
w_i^k	Demand in location i for institution k.
A_j^l	The number of current kernels in the HCU of institution l located in j. A value of A_j^l equal to zero indicates there is no current HCU at that place, and therefore, it is a potential site for installing a HCU.
F_j^l	Maximum number of kernels that can be installed in location j for a HCU of institution l.
G^l	Minimum percentage of capacity to be allocated in each HCU of institution l.
P^l	Maximum percentage of capacity in a HCU of institution l that can be shared to the demand of other institutions.
H^l	Maximum number of additional kernels of institution l that can be installed.

Decision variables:

x_{ij}^{kl}	Fraction of demand at location i from institution k allocated in a HCU of institution l located at j.
y_j^l	Integer variable equal to the number of additional kernels to be opened in a HCU located in j of institution l.

The model is then given by:

$$\text{Minimize} \qquad f(x,y) = \sum_{i \in N} \sum_{j \in M} \sum_{k,l \in K} w_i^k d_{ij} x_{ij}^{kl} \tag{1}$$

$$\text{subject to:} \qquad \sum_{j \in M} \sum_{l \in K} x_{ij}^{kl} = 1 \qquad i \in N,\ k \in K \tag{2}$$

$$\sum_{i \in N} \sum_{k \in K} w_i^k x_{ij}^{kl} \leq (A_j^l + y_j^l) C \qquad j \in M,\ l \in K \tag{3}$$

$$\sum_{i\in N}\sum_{k\in K} w_i^k x_{ij}^{kl} \geq (A_j^l + y_j^l)G^l \qquad j\in M,\ l\in K \tag{4}$$

$$\sum_{i\in N}\sum_{k\in K: k\neq l} w_i^k x_{ij}^{kl} \leq P^l(A_j^l + y_j^l)C \qquad j\in M,\ l\in K \tag{5}$$

$$A_j^l + y_j^l \leq F_j^l \qquad j\in M,\ l\in K \tag{6}$$

$$\sum_{j\in M} y_j^l \leq H^l \qquad l\in K \tag{7}$$

$$x_{ij}^{kl} \geq 0 \qquad i\in N, j\in M,\ k,l\in K \tag{8}$$

$$y_j^l \in \mathbb{Z}^+ \qquad j\in M,\ l\in K \tag{9}$$

The objective function (1) minimizes the sum of all demand allocated to each healthcare unit multiplied by its distance. Constraints (2) ensure that all demand of each location is allocated. Constraints (3)-(7) are used to define and to control the allocation of capacity. In constraints (3), the sum of demand allocated to each HCU must be equal or lower than its maximum capacity that is determined by its number of kernels $(A_j^l + y_j^l)$. Constraints (4) ensure a minimum percentage of allocated demand for each HCU based on its available capacity. Constraints (5) are used to control the percentage of demand of other institutions allocated to a HCU, this percentage is defined by each institution. The maximum number of kernels of a HCU is limited by constraints (6). The total number of new kernels to be opened by institutions is fixed in constraints (7). Finally, the nature of the decision variables is given by (8)-(9).

This problem is $\mathcal{NP}$-hard. This can be argued as follows. First, feasibility can be clearly checked in polynomial time as there are a polynomial number of variables and constraints. Thus the problem is in $\mathcal{NP}$. Then, if we take a special case of our problem by setting $A_j^l = 0$ and $F_j^l = 1$ for all $j \in M,\ l \in K$; and $G^l = 0$ and $P^l = 1$ for all $l \in K$; assuming that the fixed costs of opening candidate facilities are zero, we are left with a Capacitated Plan Location Problem (CPLP), which is known to be $\mathcal{NP}$-hard [28]. That is, CPLP is polynomially reducible to our problem, and hence it follows that our problem is $\mathcal{NP}$-hard.

3.2 Assumptions

Some assumptions of the model are discussed next. Note that x_{ij}^{kl} are continuous variables because some localities in a real scenario have more demand than capacity. Therefore, the demand may be allocated to more than one HCU. To consider the use of binary variables for the allocation is required that INEGI divides these localities into smaller basic geographic areas with lower demand than the current ones.

The idea of integrating all public healthcare institutions has been proposed by the government of many countries, and some initiatives have been carried out in isolation. Since each institution attends a different segment of the population, it is challenging to integrate the population into a single institution. Nevertheless, collaboration is possible when there is enough capacity to provide a service. In the introduced model, the capacity of each HCU can be shared to satisfy the demand of other institutions. This level of sharing is determined by each institution.

It is assumed that only one HCU can be installed in each location. In most of the cases, this assumption is valid, but in some places with high population density such as cities, more than one facility could exist. However, we can consider them as in single variable, adding up their capacities in the model.

This model does not allow to reduce the actual capacity of HCU. This assumption could help to redistribute capacity among HCUs, but the cost in a real situation would be impractical.

For instance, with a large quantity of idle capacity, a solution could suggest that some existing HCU might not be used. These solutions are not realistic in real situations because this would imply to close or transfer existing capacity and resources to another place with considerable additional costs. Therefore, constraints (4) are required to guarantee a minimum level of service for all HCUs.

4 A Case Study in the State of Mexico

In this section, we analyze a case study in the State of Mexico. To this purpose, real-world data taken from Mexican databases are used. The size of instances is defined by the sanitary jurisdictions that are the territorial sections in which the management of resources is regulated by the public healthcare institutions. These jurisdictions are integrated by a number of municipalities. We proposed the regionalization of HCUs by jurisdictions instead of municipalities to have more alternatives in the allocation of demand. The jurisdictions are separated into two groups, as shown in Table 1 and discussed in Section 1. The distribution of locations and current HCU of the foremost healthcare institution in 2019 is shown in Figure 2. We analyzed the allocation of 4,422 localities out of a total of 5,262, which is 84% of total localities in the state.

Some additional assumptions are required to apply the integer programming model to the available data. They are listed below:

- The centroid point of each locality was used to evaluate distance; this was obtained from INEGI [17].
- It is assumed that HCUs are located at the centroid point of each location.
- Distance between locations is computed using Euclidean distance between centroids.
- Demand is estimated based on INEGI [17], with projection to 2019 according to CONEVAL

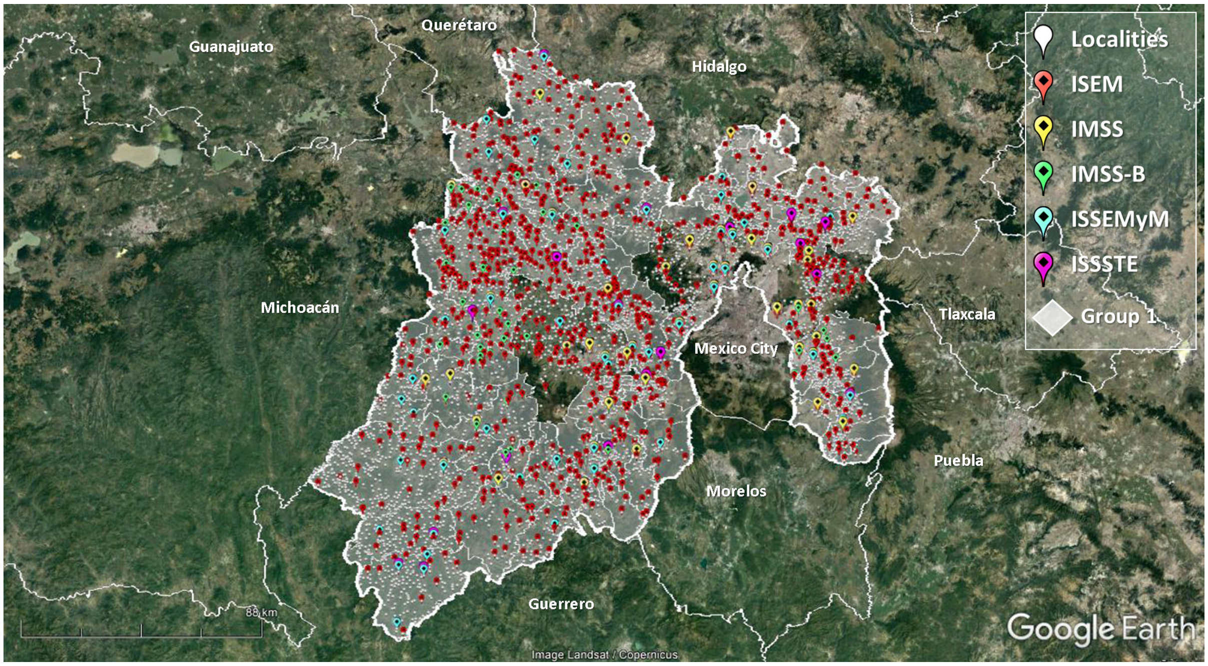

Figure 2: A map of the State of Mexico showing the demand areas and HCU locations.

- Demand of each institution is evenly distributed among localities according to the global percentage of affiliated demand of each institution by municipalities, obtained from INEGI [18].
- Additional kernels are considered for instances with over-demand, according to the demand not covered by each institution.
- For rural locations, the maximum number of kernels was fixed to 3, and for urban locations were fixed to 12, according to Secretaría de Salud [37]. The HCUs which already had capacity exceeding these limits maintained their current values of kernels.
- Rural locations with low demand rates are not considered as candidates for installing a new HCU.
- Constraints (4) and (5) are not considered in this assessment, but a sensitivity analysis is conducted for each set of them.

In Table 2, the capacity (Cap) and demand (Dem) in thousands of inhabitants for each institution and jurisdiction are shown. This information is used as input in the forthcoming experiments. Since ISEM and IMSS-Bienestar attend the same segment of the population, there is a single column for the demand for both of them. They were considered as a unique institution in the experiments. IMSS, ISSSTE, and ISSEMyM have their demand. In the last three columns, the sum of capacity and total demand, and the difference of capacity minus demand for each jurisdiction, are displayed. Each jurisdiction (row) is associated with a problem instance. As we can see, there are two types of instances. Type 1 instances (1 to 6) present excess of capacity. Type 2 instances (7 to 11) present a deficit of capacity. These types are handled differently as the needs are different, as it will be shown in the following experiments.

Table 2: Capacity and demand (in thousands of inhabitants) for institutions in each jurisdiction.

Instances			ISEM	IMSS-B		IMSS		ISSSTE		ISSEMyM		**Total**		
Type	#	Jurisdiction	Cap	Cap	Dem	Cap	Dem	Cap	Dem	Cap	Dem	Cap	Dem	Diff
1	1	Ixtlahuaca	690	24	519	27	30	12	6	36	11	789	566	223
	2	Jilotepec	366	3	237	30	18	18	5	45	5	462	265	197
	3	Tejupilco	285	9	198	9	3	18	3	78	9	399	213	186
	4	Valle de Bravo	336	39	297	33	11	6	3	45	3	459	314	145
	5	Atlacomulco	336	15	240	21	16	12	7	15	14	399	277	122
	6	Tenancingo	378	15	386	27	12	12	6	96	18	528	422	106
2	7	Tenango del Valle	294	0	305	45	70	6	11	33	18	378	404	-26
	8	Teotihuacán	216	0	276	15	68	21	18	18	5	270	367	-97
	9	Xonacatlán	459	0	532	117	190	18	20	54	19	648	761	-113
	10	Amecameca	627	24	1,098	402	355	36	77	105	21	1,194	1,551	-357
	11	Zumpango	267	0	540	72	352	12	58	9	19	360	969	-609
		Total	4,254	129	4,629	798	1,126	171	214	534	142	5,886	6,109	-223

4.1 Experimental Design

In the following paragraphs, the classifications of instances, how to interpret the solutions, and the scenarios tested in the instances are described.

Types of instances. The number of additional kernels can be estimated from the last column of Table 2. For instances 1 to 6, the problem consists in only allocating the current capacity since not additional capacity is required. This type of instances is named as instance type 1. Instances 7 to 11 require additional capacity to cover all demand. The solution to the problem will determine where to install additional capacity while the total distance traveled (TDT) of allocated demand points is minimized. This type of instances is referred as type 2.

Analysis of solutions. Two aspects are considered: (1) the distance between population and HCUs, and (2) the utilization rate of HCU. We define the utilization rate (UR) as the percentage of demand regarding to the capacity of each HCU. To evaluate the distance, the TDT, and distribution of the population by ranges of distance will be presented. To evaluate the UR, the mean, the standard deviation, and the distribution of UR between HCUs will be presented. In a high-quality solution, the distance from demand points to HCUs must be low-rate to improve access to healthcare services, and the UR must be at the same level in all HCUs to balance the workload of the HCUs.

Type of scenarios. Scenario 1: the capacity of a kernel is fixed to 3,000 people, as defined by the Health Ministry of Mexico. For instances 7-11, the number of additional kernels is fixed according to the missing demand of each institution. Scenario 2: the capacity of a kernel is determined by dividing the total demand among the available number of kernels with a small tolerance. The differences in data applied to each scenario are shown in Table 3. Scenario 1 provides the natural solution of the problem, while Scenario 2 presents a sensitivity analysis when the capacity of the kernels is modified.

Table 3: Differences of data between Scenario 1 and 2.

Scenario	Parameters	Instances										
		Type 1						Type 2				
		1	2	3	4	5	6	7	8	9	10	11
1	Kernel Capacity (C)	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000
	H^1	0	0	0	0	0	0	4	18	19	109	92
	H^2	0	0	0	0	0	0	7	16	19	0	93
	H^3	0	0	0	0	0	0	0	0	0	0	3
	H^4	0	0	0	0	0	0	2	0	1	10	15
2	Kernel Capacity (C)	2,200	1,800	1,700	2,100	2,100	2,500	3,300	4,100	3,600	3,900	8,100
	H^1, H^2, H^3, H^4	0	0	0	0	0	0	0	0	0	0	0

The instances are solved by using the branch-and-bound algorithm from the CPLEX callable library, version 12.8, with a C++ API. All instances were optimally solved in less than one hour of CPU time.

4.2 Analysis of Scenario 1

The capacity of all instances is fixed to 3,000 inhabitants by each basic kernel. The results of the solutions associated with the travel distance of demand are shown in Table 4, and the outcomes relate to the utilization rates of HCUs are shown in Table 5.

The first three columns of Table 4 indicate the distance range (km), and the following 11 columns indicate the percentage of demand that travels a distance in each range from their demand points to their HCUs for each instance. For example, for instance 1, 60.6% of demand travel between 0.0 and less than 0.5 km of distance to access their HCUs, 4.9% of demand has to travel between 0.5 and less than 1.0 km, and so on. The classification of the 11 instances by their type of instance is in the second row, and the third row shows the kernel capacity to compare solutions of Scenario 2. The worst-case rows (WC) indicate the largest distance from a demand point to its HCU, with its corresponding demand proportion shown in the following row. The last row indicates the objective function value (TDT) for each instance. Table 6 has the same interpretation, but for Scenario 2.

As can be seen from the table, the allocated distance for the majority of demand points is very reasonable. 62% of the population on average is within 500 meters to their HCUs, and 94% of the population on average is located within 5 km from its assigned HCUs. The amount of people that travel more than 10 kilometers is lower than 0.2% of the total demand in all instances except for instances 6 and 8 with 2.6% and 1.4% of demand, respectively.

The results related to the utilization rates (URs) are presented in Table 5. The kernel capacity, used as a parameter in this experiment, is shown in the header (fourth row). Each row represents

Table 4: Scenario 1. Distance distribution as percentages of demand.

			Instances										
			Type 1						Type 2				
			1	2	3	4	5	6	7	8	9	10	11
	Kernel Capacity		3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000
Distance (km)	From:	to: (<)	Percentage of Demand (%)										
	0	0.5	60.6	56.9	44.5	49.1	67.0	48.2	72.1	66.6	61.8	81.7	73.6
	0.5	1	4.9	1.6	2.7	5.0	3.9	4.6	6.1	0.3	3.6	1.4	3.0
	1	3	26.9	24.8	27.1	32.2	21.6	19.3	13.0	17.0	13.5	6.3	11.8
	3	5	5.2	12.4	19.0	10.3	7.3	12.2	6.7	8.0	6.5	5.1	9.7
	5	10	2.4	4.3	6.6	3.4	0.2	13.0	2.0	6.8	14.4	5.3	1.8
	10	-	0.00	0.05	0.09	0.00	0.00	2.56	0.06	1.37	0.19	0.20	0.19
WC	Distance (km)		8.8	10.1	11.4	8.3	6.0	16.6	13.5	17.6	10.5	18.9	10.2
	Demand (%)		0.038	0.046	0.004	0.067	0.040	0.355	0.002	0.152	0.191	0.008	0.097
	TDT ($\times 10^8$)		4.7	3.3	3.7	3.9	1.9	8.9	2.8	4.8	12.0	10.3	7.9

a specific UR range. For example, for instance 1, there are 3 HCUs with an UR between 0 and 10%, and there are 74 HCUs in the range between 90% and 100% of UR. The number of total HCUs is 153. The average UR for instance 1 is 76%, with a standard deviation of 0.279. For instances type 2, new HCUs are opened, in the Number of HCUs row the initial HCU is presented in parenthesis. As can bee seen, for type 1 instances, we found more dispersion in the utilization rates of the HCUs than the ones found in type 2 instances. This is due to the slack in the use of capacity as it is observed in the last column of Table 2 for type 1 instances. Since the capacity of the type 2 instances is just the required to meet all demand, there is no space for under-utilization of capacity. We can conclude that the variation of the UR depends on the amount of idle capacity in the system.

Table 5: Scenario 1. Utilization rate distribution of HCUs.

			Instances										
			Type 1						Type 2				
			1	2	3	4	5	6	7	8	9	10	11
	Kernel Capacity		3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000	3,000
Ranges of UR	From:	to: (<)	Number of facilities										
	0	10%	3	4	5	4	3	2	0	0	0	0	1
	10%	20%	4	4	4	0	4	0	0	0	0	0	0
	20%	30%	7	2	6	0	2	9	0	0	0	0	0
	30%	40%	7	7	10	0	4	5	1	1	0	1	0
	40%	50%	10	11	13	0	7	8	0	0	1	0	0
	50%	60%	12	12	13	0	10	4	1	0	0	0	0
	60%	70%	10	5	8	0	11	5	0	0	1	0	0
	70%	80%	8	7	9	0	8	5	1	1	0	0	0
	80%	90%	18	6	4	0	9	2	2	1	1	0	1
	90%	100%	74	25	14	222	28	73	55	44	84	81	105
	Number of HCUs		153	83	86	226	86	113	60 (48)	47 (42)	87 (69)	82 (40)	107 (41)
	Average UR (%)		76	64	56	67	69	81	97	98	99	99	99
	Standard Deviation		0.279	0.294	0.282	0.31	0.277	0.286	0.111	0.101	0.072	0.068	0.011

4.3 Analysis of Scenario 2

For Scenario 2, the results of the allocated distance are presented in Table 6, and the result for the utilization rates are shown in Table 7. The objective is to compare the characteristics of the solutions regarding Scenario 1. The capacity of a kernel is shown in the header of both tables. The capacity of a kernel is reduced for type 1 instances, and the capacity is increased for type 2 instances.

For type 1 instances, the utilization rates are more balanced than the results of Scenario 1. However, the TDT is increased to double the original value in almost all cases. For this type of instance, we conclude that variation of the UR can be adjusted, modifying the kernel capacity to balance the workload of the HCUs but with a negative impact in the TDT. For type 2 instances, the UR values are quite similar in both scenarios, since in both cases, the total capacity is very close to the total demand to cover. However, additional kernels are used in Scenario 1 to cover all unmet demand, while the kernel capacity is increased in Scenario 2 to cover the same demand with fewer HCUs. Therefore, with fewer options of HCUs under Scenario 2, the TDT is also increased compared to Scenario 1, and most of the HCUs have over-demand since the recommended value must be 3,000 inhabitants by kernel unit.

The distance of traveling is increased in Scenario 2 compared with the results of Scenario 1. For example, the percentage of people that is located between 0 to 5 kilometers to their HCUs decreases on average from 94% in Scenario 1 to 79% in Scenario 2. The percentage of people that travel more than 10 kilometers increases from 0.42% to 9.9%. For type 1 instances, the distance of traveling is increased because there is less slack in the allocation of demand points to HCUs due to the reduction of the kernel capacity. For type 2 instance, the same occurred due to there are fewer HCUs for the allocation of demand.

In conclusion, if there is enough budget to open new kernels to cover all demand, the kernel capacity can be increased in the model to allocate all demand points, but HCUs will have an overload of patients. On the other hand, if the current capacity is enough to cover all demand, the addition of new kernels will reduce the TDT in the system.

4.4 Relationship between distance and utilization rate

There is a relationship between the TDT of demand and the utilization rates of the HCUs. To get insight into this effect, we solve the problem with different values for the capacity of a kernel for instances 1, 2, 4, 5, and 6.

The results are presented in Figure 3. The TDT is the optimal value of the objective function of each instance. All values are normalized, assuming 1 for the lowest TDT, and the other values are considered as a factor of this. Augmenting the capacity of a kernel increases the capacity of the

Table 6: Scenario 2. Distance distribution as percentages of demand.

			Instances										
			Type 1						Type 2				
			1	2	3	4	5	6	7	8	9	10	11
	Kernel Capacity		2,200	1,800	1,700	2,100	2,100	2,500	3,300	4,100	3,600	3,900	8,100
Distance (km)	From:	to: (<)	Percentage of Demand (%)										
	0	0.5	55.6	51.6	43.8	48.1	62.2	47.3	67.7	59.7	50.9	81.1	53.8
	0.5	1	4.0	1.1	2.6	2.7	2.0	3.4	6.4	0.3	2.2	0.5	0.7
	1	3	22.0	16.7	18.3	20.0	12.8	11.5	11.1	1.5	10.3	1.5	4.2
	3	5	9.3	11.3	16.1	11.2	8.9	8.9	5.6	3.7	6.7	0.7	9.0
	5	10	8.9	9.0	12.7	12.5	8.8	13.1	6.4	10.5	22.2	11.1	6.2
	10	-	0.2	10.3	6.5	5.5	5.2	15.7	2.8	24.4	7.7	5.0	26.0
WC	Distance (km)		13	35	20.8	20.8	19.7	27.6	13.5	30.1	29.7	28.1	30.9
	Demand (%)		0.04	0.05	0.50	0.15	0.01	0.11	0.002	0.51	0.003	0.17	0.03
	TDT ($\times 10^8$)		7.9	8.8	6.1	7.8	5.3	15.9	5.4	17.5	29.4	25.0	49.4

Table 7: Scenario 2. Utilization rate distribution of HCUs.

			Instances										
			Type 1						Type 2				
			1	2	3	4	5	6	7	8	9	10	11
	Kernel Capacity		2,200	1,800	1,700	2,100	2,100	2,500	3,300	4,100	3,600	3,900	8,100
Ranges of UR	From:	to: (<)	Number of facilities										
	0	10%	0	0	1	0	0	0	0	0	0	0	0
	10%	20%	1	0	0	0	0	0	0	0	0	0	0
	20%	30%	1	0	0	0	0	2	0	0	0	0	0
	30%	40%	0	0	0	2	0	3	0	0	1	0	0
	40%	50%	0	0	1	0	0	3	0	0	1	0	0
	50%	60%	0	2	3	0	0	2	1	1	3	1	0
	60%	70%	1	5	1	1	1	0	1	0	0	0	0
	70%	80%	1	1	4	2	0	2	1	0	1	0	0
	80%	90%	2	3	5	0	0	1	2	0	0	0	1
	90%	100%	138	72	71	85	85	100	43	44	69	61	40
	Number of HCUs		144	83	86	90	86	113	48	45	75	62	41
	Average UR (%)		98	96	94	98	100	94	97	99	96	99	99
	Standard Deviation		0.101	0.109	0.154	0.103	0.036	0.176	0.092	0.073	0.128	0.051	0.028

system. Therefore, the TDT can be reduced as it is shown in the left-chart. Moreover, the slack in the capacity of the system causes a high variation in the utilization rates as it was shown in the right-chart.

For instances with slack in the capacity, the kernel capacity can be adjusted to control the variation of utilization rates. If we reduce the tolerance in the allocating options, we can homogenize the workload in HCUs, but this has an important cost in the TDT.

4.5 Sensitivity analysis for P^l

A limit in the percentage of capacity shared with other institutions is used for institutions where affiliated users pay a fee to get access to healthcare services. The institution primarily must ensure the service coverage for their users, and only if there is slack in the capacity, this can be shared with other institutions. If there is no excess capacity for institution l, the percentage of P^l must be zero. The effect in solutions for modifying this percentage is determined with an experiment conducted for instances 1, 2, 4, 5, and 6. The P^l was set to values between 0 and 1 for institutions

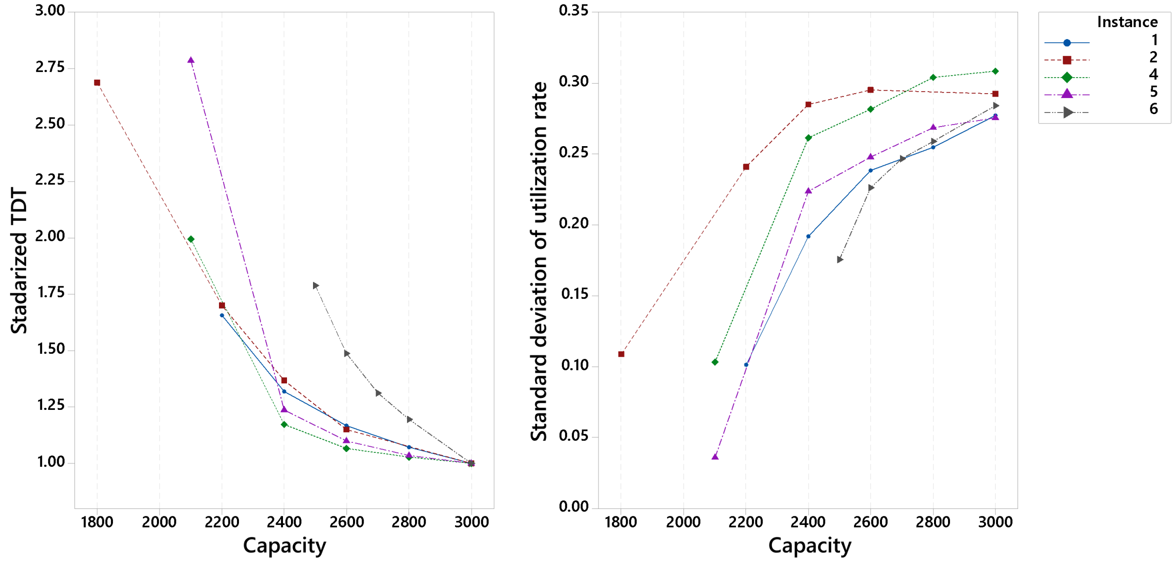

Figure 3: Comparison of total distance traveled and utilization rate.

2, 3, and 4 (institution 1 is open to all users).

The TDT and the standard deviation of the utilization rates are shown in Figure 4. In general, the TDT was reduced when the value of P^l was close to 1 because, in that case, constraints 5 are omitted, and the solution space is more extensive. The impact in the TDT is entirely different for each instance. For example, for instance 6 the increase of the TDT was almost 1.8 larger than the best TDT, and for instance 5, the increment was only 1.006 as large than the best TDT. On the other hand, the standard deviation of the utilization rates did not show a generalized pattern. Therefore, we conclude that there is no direct relationship between P^l and the variation of the utilization rates.

4.6 Sensitivity analysis for G^l

This value is used to fix a lower bound in the utilization rates of all HCUs of institution l. When capacity is near to demand, constraints (4) are not necessary. However, when capacity is considerably larger than the demand, these constraints will help institutions to work at least at a minimum rate in all HCUs. Different values of G^l are tested for all institutions to measure the effect in the TDT and the standard deviation of utilization rates.

The results for instances 1, 2, 4, 5, and 6 are shown in Figure 5. As it can be seen, the TDT has an explosive growth when the values of G^l are increased from 0 to 0.5, while a nonlinear decline is observed in the standard deviation of the URs of the HCUs. The values of G^l must be carefully set by decision-makers since, at some point, an unfeasible solution could be reached.

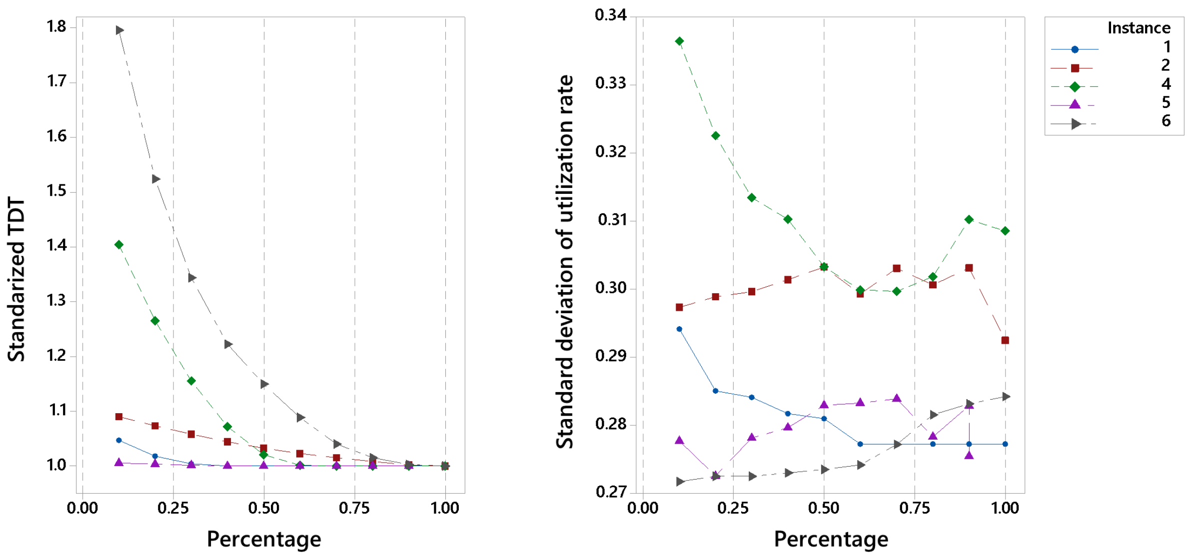

Figure 4: Results for different values of P^l.

5 Conclusions

In this paper, we have addressed a problem of locating and upgrading primary healthcare units within a multi-institutional public system A novel integer programming model was introduced fro providing a more efficient regionalization of the resources. The problem is motivated by a real-world application in the Mexican Healthcare System.

This study can be used as an essential preventive strategy to deal with the main causes of death and to improve the quality of people's life that suffer chronic degenerative diseases. The optimization of the total distance traveled by the population can help to improve access to the services. In contrast, the assurance and proper distribution of the healthcare capacity can help improve the quality of the service.

The proposed model incorporates an inter-institutional collaboration to share the capacity, and the location of additional capacity to improve the coverage of primary healthcare services. The standardization of capacity allows to integrate into the same planning scheme all the healthcare institutions.

The case study in the State of Mexico allowed us to find interesting results. When capacity is enough to meet demand, the allocated distance from locations to HCUs is very short. However, the minisum objective could discriminate some locations with low demand rates. In the implementation of this solution to a real scenario, these locations could be reallocated to a near HCU if the level of demand does not represent a significant additional workload for HCUs. In other words, the solutions to the integer programming model are only a guide for the planning more than a strict

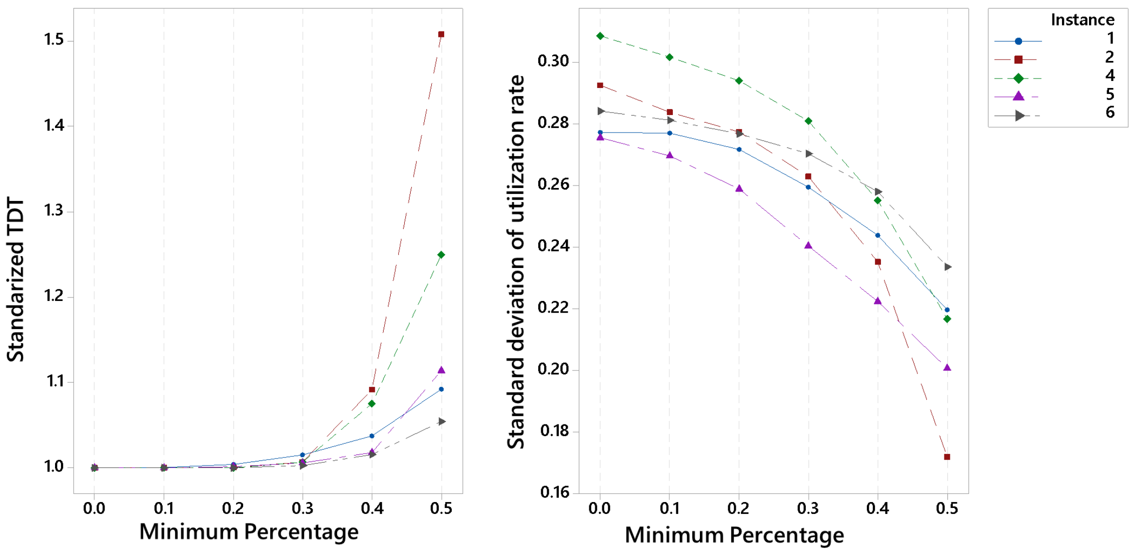

Figure 5: Results for the minimum values of utilization rate.

rule to follow.

The variation in utilization rates between HCUs was observed when the values of capacity and demand were very distant from each other. In these cases, constraints (4) can be used to set a minimum utilization rate at each HCU, and at the same time, the variation is reduced.

The modification of the kernel capacity can be used in two situations: (i) To reduce the variation of the utilization rate of HCUs when capacity is larger than the demand, and (ii) to find a feasible solution when demand is greater than capacity. The addition of capacity is an opportunity to improve the TDT, but this depends on the available budget of each institution.

The potential use of this model can be extended country-wise, since the data required to apply the model, it can be obtained by the population census and the reports of infrastructure resources of each institution. The use of a distance matrix API could improve the precision of solutions concerning a real application.

There are several avenues for future work. An important improvement in the solution can be made if a more extensive set of municipalities is integrated into a single problem instance. In the case of the State of Mexico, there are 5,262 locations, but some of them require a more specific partition due to their high population density. Naturally, if the proposed model proves unsolvable for such large instances, heuristic methods might be needed.

The model can also be extended by seeking the integration of multiple services at some HCU, such as gynecology, pediatrics, and dental care. Alternative or additional objectives could be evaluated such as the minimization of fixed and variable costs, or the maximization of coverage. Altough the model arises from a real-world application in the Mexican Healthcare system, it certainly has features that may make it useful in developing countries.

Acknowledgments: The research of the first author was supported by a PRODEP Postdoctoral Fellowship (No. 511-6/2019-15111).

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A Summary of Literature Survey on Healthcare Location

In this appendix, we present in Table 8 an extension of literature on healthcare location from the computational perspective originally presented by Ahmadi-Javid et al. [2] for primary care facilities (hospitals, clinics, off-site public access devices, etc.) We have added the works from lines 26 to 33. The definition of each term shown in every cell is given in Table 9.

Table 8: Survey on non-emergency healthcare facility location.

No.	Reference (year)	UNC	Multi-period	Model settings	Objective function	Decision variables	Constraints	Location model	Modeling approach	Solution method	Case study
1	[5] (2000)	N	S	P1, P12	O10	D1, D2	C1, C4, C9-1, C9-2, C11	SCL	MILP, GP, MCDM	SL	Y
2	[21] (2001)	N	S	P1, P3, P5-1, P5-2	O7	D1, D4	C4, C5, C10, C11	MCL	ILP	SC, H	Y
3	[10] (2002)	N	S	P1, P3, P8, P11, P12	O3	D1, D8	C1, C4, C9-1, C10	PML	MILP	SC, LR	Y
4	[22] (2004)	Y	S	P1, P3, P5-1, P5-2, P8, P12	O7	D1, D4	C4, C5, C10, C11	MCL	ILP, O(QT)	SC	N
5	[42] (2004)	N	D-2	P3, P4, P5-2, P7, P12	O3, O4, O9, O10	D7, D8	C9-1	FCL	MILP, MCDM	MH-TS	Y
6	[29] (2006)	N	S	P1, P3, P4	O3, O5	D1, D4	C1, C4, C5, C8, C9-1	PML	MILP, MCDM	SX	Y
7	[8] (2006)	Y	S	P1, P3, P4	O10	D4, D8	C4, C9-1, C9-2, C11	O	PSP, MINLP	SO	Y
8	[31] (2008)	N	D-1	P1, P5-1, P5-2	O4	D1, D4, D8	C1, C4, C9-2	FCL	ILP	SL	Y
9	[13] (2008)	N	S	P1, P4, P5-1, P5-2, P8	O7	D1, D4, D8	C5, C9-1, C10, C11	MCL	MILP	–	Y
10	[34] (2009)	N	S	P1, P3, P5-1, P5-2, P11	O9	D1, D4, D8	C4, C5, C10	MCL	MILP	SO	Y
11	[40] (2009)	N	S	P1, P3, P11, P12	O10	D1, D4	C4, C5, C11	O	ILP	SX	Y
12	[26] (2012)	N	S	P1, P2, P4, P8, P11, P12	O3	D1, D4, D7, D8	C1, C5, C9-1, C9-2, C11	PML	MILP	SG	Y
13	[38] (2012)	N	S	P1, P3, P4	O7	D1, D4	C1, C4, C5, C9-1	MCL	ILP	SC, MH-GA	Y
14	[15] (2012)	N	S	P1, P3, P4, P7, P9	O3/O6/07	D1, D4, D7	C1, C4, C8, C9-1, C9-C11	MCL	ILP	–	Y
15	[6] (2012)	N	S	P1, P3, P5-1, P5-2	O3	D1, D4, D8	C1, C10, C11	FCL	MILP	SC	Y
16	[41] (2013)	N	S	P1, P3, P8, P11, P12	O3, O10	D1, D4	C1, C4, C5, C11	PML	ILP, MCDM	SX	Y
		N	N	P1, P3, P8, P11, P12	O7, O10	D1, D4, D5-1	C4, C5, C11	MCL	MILP, GP, MCDM	SX	Y
17	[30] (2013)	Y	S	P1, P3, P8, P12	O3, O10	D1, D4, D8	C1, C5, C9-2	PML	MILP, PSP, MCDM	SX	Y
18	[19] (2013)	N	S	P1, P3, P5-1, P8, P12	O7	D1, D4	C5, C9-1, C10, C11	MCL	ILP	SC, LR	Y
19	[11] (2013)	N	D-2	P1, P3, P5-1, P5-2, P12	O4	D1, D4, D8	C1, C10, C11	FCL	MINLP	SC, MH-SA, H	Y
20	[3] (2014)	N	S	P1, P3, P5-1, P12	O3/04/O10	D1, D4, D8	C1, C4, C9-1, C9-2	PML	MILP, MCDM	MH-GA	Y
21	[33] (2014)	Y	S	P1, P2, P4, P5-1, P5-2	O4, O10	D1, D4	C1, C4	FCL	INLP, 2-SSP, MCDM	SG, MH-O	Y
22	[12] (2014)	N	S	P1, P3, P5-1, P5-2, P8, P12	O3, O4, O10	D1, D4	C1, C5, C9-2	FCL	MILP	SC	Y
23	[27] (2015)	Y	D-2	P1, P2, P5-1, P5-2, P5-3, P8, P11,P12	O3, O4, O9	D1, D7, D8	C4, C5, C9-1, C9-2	FCL, MCL	MILP, 2-SSP,MCDM	SG	Y
24	[39] (2015)	Y	S	P1, P3, P4, P5-1, P5-2, P12	O4	D1, D4, D8	C4, C9-1, C10, C11	FCL	MILP, RO	SG	Y
25	[32] (2016)	N	S	P1, P2, P12	O10	D1, D8	C4, C11	O	MILP	O	Y
26	[4](2012)	N	S/D-2	P1, P3, P4, P5-1, P5-2, P5-3, P12	O4	D1, D4	C4, C5, C8, C9-1, C11	FCL	ILP	SL	Y
27	[43](2012)	Y	S	P1, P3, P4, P5-1, P5-2, P5-3, P12	O4	D1, D4, D7	C4, C5, C8, C9-1, C9-2, C11	FCL	ILP	SC	Y
28	[14](2016)	N	S	P1, P3, P4, P8, P12	O1/ O3/ O7	D1, D4, D5-1, D7	C1, C4, C5, C8, C9-1, C11	PML/MCL	ILP	–	Y
29	[46](2016)	N	S	P1, P2/P3, P4, P5-1,	O4, O9, O10	D1, D8	C9-1	O	NLP	MH-GA	Y
30	[44] (2019)	Y	S	P8, P12	O7	D1, D5-2, D8	C4, C11	MCL	SP-O	MH-GA	Y
31	[25][24](2019)	N	D-2	P1, P4, P5-1, P5-2, P5-3, P7, P8, P12	O4	D2, D4, D8	C9-1, C9-2, C11	FCL	ILP	SC	N
32	[1](2020)	Y	S	P1, P3, P4, P5-1, P5-2, P6, P8, P12	O4	D1, D2,D7	C5, C6, C9-1, C11	FCL	INLP	SC	N
33	This paper	N	S	P1, P2, P4, P7, P12	O3	D1, D4	C4, C8, C9-1	PML	ILP	SC	Y

Sources: From No. 1 to 25 the reviews were obtained from Ahmadi-Javid et al. [2].

Table 9: Definition of terms in Table 8.

Specific feature	Code	Description
(UNC) Consideration	Y	Considering uncertainties
of uncertainty	N	Not considering uncertainties
Multi-period setting	S	Static
	D-1	Dynamic: Multi-period short-term decisions(e.g.,ambulance deployment or shift resource allocation)
	D-2	Dynamic: Multi-period long-term decisions(e.g., location)
Model settings	P1	Demand
	P2	Travel time
	P3	Travel distance
	P4	Facility capacity
	P5-1	Fixed cost
	P5-2	Variable cost
	P5-3	Penalty for lost demand
	P6	Waiting time
	P7	Multiple servers :Considering several servers at each facility
	P8	Multiple services/ Multi-type demand
	P9	Elastic demand: Demand depends on distance, waiting time, etc.
	P10	Busy fraction: Probability of an ambulance being busy
	P11	Hierarchical system
	P12	Other items, e.g.,number of periods and different coefficients
Objective function	O1	Minimize total number of facilities
	O2	Minimize total number of ambulances
	O3	Minimize total travel distance (or time)
	O4	Minimize sum of costs
	O5	Minimize maximum travel distance (or time)
	O6	Maximize participation
	O7	Maximize demand coverage
	O8	Maximize multiple coverage
	O9	Minimize number of uncovered demand
	O10	Other objectives, e.g., maximize number of voluntary facilities, minimize number of ambulance relocations, and minimize maximum transfer time between stations
Decision variable	D1	Location of facilities
	D2	Allocation of resources
	D3	Deployment (location or relocation) of ambulances in stations
	D4	Allocation of HCFs to demand points
	D5-1	Demand coverage: Once

Table 9: (continued)

	D5-2	Demand coverage: More than once
	D6	Dispatch (assignment) of ambulances to demand points
	D7	Number of required resources
	D8	Other items, e.g., demand flow and number of required facilities
	C1	Full coverage
Constraints	C2	Partial coverage
	C3	Multiple coverage
	C4	Maximum number of required facilities
	C5	Maximum travel distance (or time)
	C6	Ambulance reliability/service level (probabilistic coverage)
	C7	Maximum number of ambulances at each station
	C8	Maximum available resources
	C9-1	Service capacity: Maximum capacity for demand response
	C9-2	Service capacity: Minimum capacity for demand response
	C10	Budget
	C11	Other items: e.g., no-vacant and flow constraints
Basic location problem	SCL	Set covering location problem
	MCL	Maximal covering location problem
	PCL	p-center location problem
	PML	p-median location problem
	FCL	Fixed charge facility location problem
	O	Other items, e.g., p-dispersion, maxisum dispersion, MNSF location problems
Modeling approach	ILP	Integer linear programming
	INLP	Integer nonlinear programming
	MILP	Mixed-integer linear programming
	MINLP	Mixed-integer nonlinear programming
	GP	Goal programming
	NLP	Nonlienar programming
	FP	Fuzzy programming
	PSP	Stochastic programming: Probabilistic (or chance-constraint) programming
	1-SSP	Stochastic programming: Single-stage stochastic programming
	2-SSP	Stochastic programming: Two-stage stochastic programming
	M-SSP	Stochastic programming: Multi-stage stochastic programming
	SP-O	Stochastic programming: Other
	DP	Dynamic programming
	SDP	Stochastic dynamic programming
	RO	Robust optimization

Table 9: (continued)

	MLP	Multi-level optimization
	CP	Constraint programming
	MCDM	Multi-criteria decision making
	MPDM	Multi-person decision making (Game Theory)
	O	Other items, such as queuing theory (QT), graph theory (GT), and network theory (NT)
Solution Method	SL	General-purpose optimization software package: Lingo
	SC	General-purpose optimization software package: CPLEX
	SX	General-purpose optimization software package: Xpress
	SG	General-purpose optimization software package: GAMS
	SO	General-purpose optimization software package: Other
	BB	Branch and bound
	BC	Branch and cut
	BP	Branch and price
	BCP	Branch and cut and price
	CP	* Cutting plane
	LR	* Lagrangian relaxation
	BD	* Benders decomposition
	DP	* Dynamic programming
	O	* Other items, such as combinatorial and randomized algorithms
	H	** Heuristic
	MH-TS	** Metaheuristics (MH): Tabu Search
	MH-GA	** MH: Genetic algorithm
	MH-SA	** MH: Simulated Anneling
	MH-AC	** MH: And Colony
	MH-O	** MH: Other items
	S-SBO	** Approximate stochastic optimization (S): Simulated-based optimization
	S-SA	** S: Stochastic approximation
	S-SAA	** S: Sample average approximation
	S-SO	** S: Scenario optimization
	S-O	** S: Others
Case study inclusion	Y	With case study
	N	Without case study

* Class A: Accurate methods (exact or bounded-error methods)

** Class B: Inaccurate methods: methods without any error analyses