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Optimization of the Healthcare Infrastructure Planning in Guanajuato: A Comprehensive Primary Healthcare Units Planning Model

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Abstract

The planning of primary healthcare infrastructure is essential for improving population access to healthcare services, especially in developing countries where access to healthcare is limited. In this work, we propose the use of a bi-objective optimization model to support the decision-making process related to the strategic decisions of locating new Primary Healthcare Units (PHUs), upgrading the installed capacity in the PHUs network, and allocating demand points to PHUs. We present a case study based on the State of Guanajuato, Mexico; a federal entity with more than 6 million inhabitants in 2020, where more than 21% of the population lacks formal healthcare insurance and the other 35% is affiliated to a public healthcare institution. The problem addressed was solved for each of the state's eight regions, with instances between 650 and 1398 demand points, generating the Pareto set for five different budget scenarios. The problem minimizes the weighted total travel distance from demand points to PHUs for general medical consultation while maximizing the demand coverage for complementary services such as nutrition counseling, dental care, mental health, clinical analysis, and imaging. An augmented version of the ϵ-constraint method is used to find the Pareto sets, and the Cplex solver is employed to solve all the generated instances. The model's usefulness is shown through its application in the case study.

Keywords
bi-objective model, healthcare planning, facility location, primary healthcare services

1. Introduction

According to the World Health Organization, universal access to high-quality medical services is fundamental for societal well-being [1]. In developing countries, healthcare disparities, marked by unequal resource distribution, limited geographical accessibility, and varying care quality, present challenges for a significant portion of the population without health insurance [2]. In Mexico, the Ministry of Health (SSA, *by its acronym in Spanish*) is crucial for healthcare, addressing public health issues by providing medical care through Primary Healthcare Units (PHUs) and hospitals [3]. However, Mexico's healthcare system is complex, reflecting factors, such as institutional divisions, limited funds, and the need to adapt to changing population needs. Optimizing resource planning is crucial to ensure medical care reaches those with the greatest need. In this context, this paper is focused on Guanajuato, Mexico, where the National Institute of Statistics and Geography (INEGI, *by its acronym in Spanish*) reported in 2020 that around 21% of the population (1.2 million) lacks formal health insurance [4]. This underscores the urgent need to address healthcare disparities. This work aims to tackle this challenge through an optimization model for locating new PHUs, considering service demand and capacity. A bi-objective mixed-integer linear programming model is proposed to enhance access to primary healthcare services by optimizing SSA's PHU investments. Services include basic medical consultations and complementary services, such as nutrition counseling, dental care, mental health, clinical analysis, and imaging. For the primary service, demand is allocated to capacitated PHUs to minimize travel distance. Complementary services aim to maximize demand coverage in specific PHUs, all this subject to a budget constraint. The problem is divided into eight regions in Guanajuato, and the Pareto set is obtained using the ϵ-constraint method. Focusing on Mexican healthcare, [5] and [6] address the critical challenge of optimizing PHUs allocation and minimizing patient travel distances. [7] propose an undisclosed mathematical modeling approach to optimize existing Primary Healthcare Centers, aiding resource allocation and network performance improvement in the face of evolving demographics and limited investments. [8] explore the efficient deployment of mobile units to enhance healthcare coverage, particularly in low-income areas. These studies provide valuable tools for optimizing healthcare facilities and resource allocation, with potential global applications. However, our contribution involves combining the Capacitated Facility Location Problem and the Maximal Covering Location Problem to address the localization of PHUs within the public sector. The obtained results provide the potential to generate effective solutions for the complex task of healthcare facility planning within the constraints of limited resources.

2. Problem Description

The following problem was based on [6]. However, in this case, we are dealing with a bi-objective problem, while in the original model, a single objective function problem was addressed, and the other objective was set as a constraint. There are two types of services: the *main service* (MS) corresponds to the outpatient service provided by a physician and the complementary services (CS) are other services available in some PHUs such as nutrition counseling, dental care, mental health, clinical analysis, and imaging. Demand for MS must be allocated in the problem to PHUs without exceeding their capacities. The objective of this service is to minimize the sum of the travel distance of all the demand. In the case of CS, the objective is to maximize the coverage of demand. To evaluate the coverage, a critical coverage radius is considered for each CS type. In the problem, there are various levels of PHU, as the level, additional capacity of the MS, and additional CS are available, but the investment cost increases. In the problem is considered the option to upgrade existing PHUs to a higher level, but also is considered the option to open new PHUs in candidate site. These decisions are limited by a budget. The notation, parameters, and variables used in the problem formulation are the following:

Sets:
M: Set of demand points; $i \in M$.
N: Set of existing PHUs and candidate locations to install new PHUs; $j \in N$.
N_A: Subset of locations such that a PHU is already installed.
N_B: Subset of locations such that a new PHU can be installed.
K: Set of PHU types; $k \in K$.
$K(j)$: Subset of PHU types to install or upgrade at location $j \in N$.
S: Set of complementary services; $s \in S$.
Parameters:
F^k: Fixed cost of installing the PHU type $k \in K$
U_j^k: Fixed cost of upgrading the PHU located at $j \in N_A$ to a PHU type $k \in K$.
B: Available budget for installing or upgrading PHUs.
D_{ij}: Distance from demand point $i \in M$ to the PHU located at $j \in N$.
P_i: Demand (number of people) of the main service and the complementary services at point $i \in M$.
C^k: Capacity (number of people) of the PHU type $k \in K$ for providing the main service.
TTD: Upper bound on the total travel distance by the demand for receiving the main service.
R^s: Critical distance of coverage for each complementary service $s \in S$.
T^{ks}: Auxiliary parameter equal to 1 if the complementary service $s \in S$ is provided by the PHUs type $k \in K$; and 0, otherwise. This parameter does not appear in the model, but it is used for computing parameters A_{ij}^{ks} showed below.
A_{ij}^{ks}: Coverage parameter equal to 1 if a PHU type $k \in K(j)$ located at site $j \in N$ covers the demand point $i \in M$ for each complementary service $s \in S$.
Decision variables:
y_j^k: Binary variable equal to 1 if the PHU type $k \in K(j)$ is located at site $j \in N$ and 0, otherwise.
x_{ij}: Binary variable equal to 1 if the demand point $i \in M$ is allocated to the PHU located at $j \in N$ for the main service; and 0, otherwise. $X_{jj} = 1$ represents a facility located at demand point j.
v_i^s: Binary variable equal to 1 if the service $s \in S$ of the demand point $i \in M$ is covered; and 0, otherwise.

$$\min \quad Z_1 = \sum_{i \in M} \sum_{j \in N} P_i \, D_{ij} \, x_{ij} \qquad (1)$$

$$\max \quad Z_2 = \sum_{i \in M} \sum_{s \in S} P_i \, v_i^s \qquad (2)$$

$$\text{st} \quad \sum_{i \in M} x_{ij} = 1 \qquad i \in M \qquad (3)$$

$$\sum_{i \in M} P_i \, x_{ij} \leq \sum_{i \in M} C^k \, y_j^k \qquad (4)$$

$$x_{jj} \geq \sum_{i \in M} y_j^k \qquad (5)$$

$$\sum_{k \in K(j)} y_j^k = 1 \qquad j \in N_A \qquad (6)$$

$$\sum_{k \in K(j)} y_j^k \leq 1 \qquad j \in N_B \qquad (7)$$

$$v_i^s \leq \sum_{j \in N_A} \sum_{k \in K(j)} A_{ij}^{ks} \, y_j^k \qquad i \in M, \, s \in S \qquad (8)$$

$$\sum_{j \in N_A} \sum_{k \in K(j)} U_j^k y_j^k + \sum_{j \in N_B} \sum_{k \in K(j)} F^k y_j^k \leq B \qquad (9)$$

$$x_{ij} \in \{0,1\} \qquad i \in M, \, j \in N \qquad (10)$$

$$y_j^k \in \{0,1\} \qquad j \in N, \, k \in K(j) \qquad (11)$$

$$v_i^s \in \{0,1\} \qquad i \in M, \, s \in S \qquad (12)$$

The first objective function (1) aims at minimizing the total travel distance of the demand to the PHU for receiving the main service. The second objective function (2) seeks to maximize the total demand coverage of the complementary services. Constraints (3) ensure that each demand point is allocated to a single facility for the main service. Constraints (4) ensure that the total demand allocated to each PHU must not exceed its capacity. Constraints (5) force to allocate demand of a site where a PHU is located. Constraints (6) ensure that an existing PHU can be upgraded to another PHU type or can remain its current type. Constraints (7) allow opening a single PHU type in a candidate's site. Constraints (8) activate the variable v_i^s if a demand point is covered by a complementary service. Constraint (9) limits the number of PHUs to be upgraded and PHUs opened in a candidate's sites according to the budget limit. Finally, the nature of the decision variables is specified by constraints (10)– (12).

3. Methodology

The problem was solved using the epsilon-constraint methodology for multi-objective optimization. The goal is to find a set of solutions that optimize the two conflicting objectives simultaneously. This method transforms a multi-objective optimization problem into a series of mono-objective problems by introducing an epsilon parameter and turning one objective into a constraint while optimizing the others. The method found in the Pareto set is the set of solutions in the decision space where no solution is superior to another in all the objectives. These solutions are considered Pareto optimal, as they represent a trade-off between objectives, and there is no way to improve one objective without degrading another. The AUGMECON method represents an enhancement of the original epsilon-constraint method and is widely recognized for its effectiveness in generating Pareto front representations. In this study, we employed AUGMECON2 [9], an improvement upon AUGMECON [10] that leverages information from slack variables in each iteration. This enhancement leads to a reduction in computation time by avoiding redundant iterations and optimizing the overall process.

4. Case Study

The problem was applied to the state of Guanajuato, one of the 32 federal entities of Mexico. This territorial unit is divided into 46 municipalities, encompassing a total of 12,340 demand points subject to this analysis. Covering an area of 30,606.7 km², the state accounts for approximately 1.6% of Mexico's total landmass. For the sources of data used in the case study, the geographic location of the demand points and their corresponding demands were obtained from INEGI [4]. Utilizing longitude and latitude data for each locality in Guanajuato, the coordinates were transformed into the Universal Transverse Mercator projection system. The existing PHUs, their types, and capacities were sourced from the official website of the Directorate General of Health Information of the SSA [11]. The fixed cost for each type of facility was extracted from the report "Resource Models for Planning Health Units" published by the Ministry of Health in 2010 [12]. It is essential to note that these costs were updated to reflect the economic conditions of the year 2023. Additionally, the cost for facility updates was estimated based on the supplementary expenses incorporated into the establishment of new facilities.

Table 1. Regional healthcare and demand data summary.

Region	Demand Points	Demand (users)	Healthcare Units	Main Service		Candidate Sites
				Capacity (users)	Utilization (%)	
1	650	219,599	64	396,000	55	20
2	1,260	570,838	81	630,000	91	35
3	1,398	365,851	63	429,000	85	100
4	1,303	497,621	69	543,000	92	69
5	988	685,565	62	687,000	100	44
6	980	328,068	47	288,000	114	32
7	963	409,419	58	480,000	85	42
8	1,362	362,808	71	432,000	84	144
Total	**8,904**	**3,439,769**	**515**	**3,885,000**	**89**	**486**

To solve the problem, the state is divided into eight regions. The territorial division plays a crucial role in this study, providing the necessary framework for analyzing regional patterns and evaluating the model's impact in various specific geographical areas. **Table 1** provides a comprehensive overview of demand points, demand quantity (users), existing healthcare units in each region, their capacities for the main service, current utilization rates, and potential candidate sites for PHU installations. Capacity is determined by considering the type of PHU multiplied by the 'basic kernel,' equivalent to the capacity to serve 3,000 users. The selection of candidate sites was based on locations not close to existing PHUs. A total of 486 candidate sites were identified throughout the state of Guanajuato.

Table 2 offers an overview of the PHU types and their respective characteristics. The second column provides details on the main service capacity, indicating the number of users each facility can permanently serve. Facility type 1 has a capacity of 3,000 users, and subsequent facility types have capacities as multiples of this value, following the 2010 guidelines set by the SSA. The availability of these services for each facility type is presented in the following five columns as binary values (1 denoting service provision and 0 otherwise). The potential to upgrade existing facilities to a higher-tier category depends on the specific type of settlement, incorporating factors such as population density, infrastructural development, and the overall needs of the community. Furthermore, the critical coverage radius (R^s) in kilometers for each complementary service is presented as a key aspect of the proposed analysis. All data of the case study is available in the following link: [*hidden for the blind review*].

Table 2. Types of PHUs and offered services.

Facility Type	MS capacity (users)	Complementary Service Coverage CS 1	CS2	CS3	CS4	CS5
1	3,000	0	0	0	0	0
2	6,000	0	0	0	0	0
3	9,000	1	1	1	0	0
4	12,000	1	1	1	0	0
5	15,000	1	1	1	1	0
6	18,000	1	1	1	1	0
7	21,000	1	1	1	1	1
8	24,000	1	1	1	1	1
9	27,000	1	1	1	1	1
10	30,000	1	1	1	1	1
11	33,000	1	1	1	1	1
12	36,000	1	1	1	1	1
Critical coverage radius (km)		5	5	5	10	10

Table 3. Selected budgets for each region (1×10^6 MXN).

Region	Budgets B1	B2	B3	B4	B5
1	439	579	859	1,138	1,418
2	714	838	1,088	1,337	1,586
3	1,062	1,315	1,821	2,327	2,834
4	1,022	1,203	1,565	1,927	2,288
5	874	934	1,054	1,174	1,294
6	595	709	939	1,169	1,399
7	731	895	1,222	1,548	1,875
8	1,354	1,651	2,245	2,839	3,434

For the empirical analysis, five different budget scenarios were generated, as shown in **Table 3.** B1 is the minimum budget to have feasible solutions and B5 is the maximum budget required to get the best possible values for both objectives (Z_1 and Z_2) given the other constraints. To obtain the value of the minimum budget (B1), the problem was solved with the objective function of minimizing the total cost removing constraint (9). For the maximum budget (B5), the problem was solved with both objective functions (1) and (2) separately, and then, the problem was solved again by minimizing the total cost with the objective functions (1) and (2) as constraints using the obtained as bounds. Then, B2, B3, and B4 represent budgets equally distributed between B1 and B5. In the ϵ-constraint method, one objective function is defined as a constraint of the problem. In this case, the objective function Z_2 was constrained. The bound of this constraint was gradually modified to generate different Pareto points. In this case, we decided to generate one hundred equidistant bounds.

To solve all integer programming models generated with the ϵ-constraint method, the Branch-and-Bound algorithm from CPLEX 20.1 solver was used, with the callable library of C++. The experiments were conducted on a computer with an Intel(R) Core (TM) i5-4590 processor running at 3.30 GHz, supported by 16 GB of RAM, and operating under Windows 10. All instances were solved with a CPU time limit of one hour obtaining optimal and near to optimal solutions in all the cases. A total of 100 iterations were attempted for each instance of the model to determine the Pareto set in each region using the AUGMECON2 method. It is crucial to note that each instance involves solving the problem in a specific region with a defined budget. There is a significant variation in the number of Pareto points found and the percentage of demand covered based on the budget invested. The average computation time was in average 286 seconds. This is a reasonable computation time, as there is no need to employ a heuristic procedure to solve the problem.

We selected two regions as examples to show the Pareto frontiers for the different budgets. These results are presented in **Figures 1** and **2**, revealing distinct behaviors for both frontiers. For instance, region 5 corresponds to the region where the City of León is located, an urban area with advanced infrastructure that already satisfies most needs, as depicted in **Figure 1**. Even with a minimum budget (B1), over 95% of the demand can be covered on average with complementary services. In contrast, in the rural region of San Luis de la Paz, classified as region 8, there is a noticeable need for more substantial investment. This is particularly evident when utilizing the maximum budget (B5) to ensure coverage of complementary services, only 90% of the demand was covered on average, as illustrated in **Figure 2**. This variability highlights the essential link between needs and budgetary amounts, determined by specific factors. Demographic differences, prevalent health conditions, geographic accessibility, socio-economic levels, and existing infrastructure play pivotal roles in this context. Larger populations or those with higher health challenges may require proportionally higher investments, while geography and socio-economic disparities also influence health demand and the need for investment. A meticulous assessment of these factors is essential to tailor health investment strategies that address the specific needs of each region.

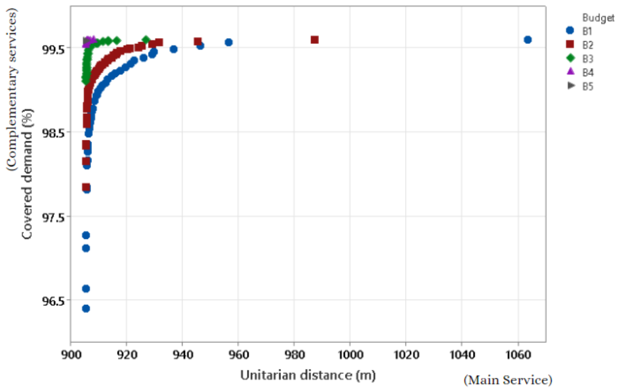


Figure 1. Representation of the Pareto Frontier of region 5.

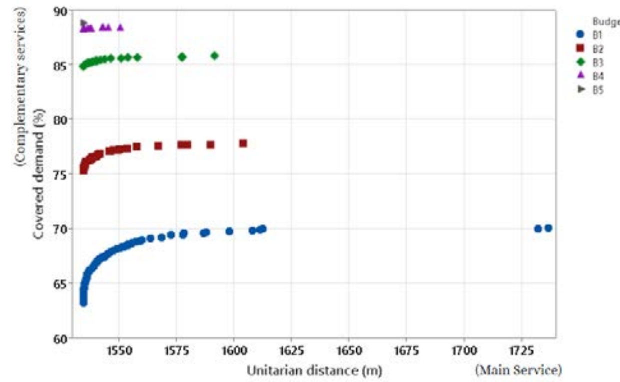
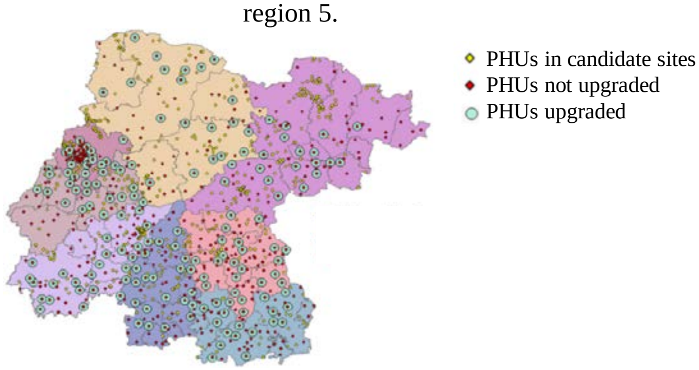
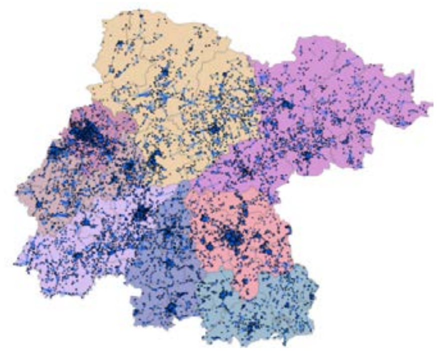


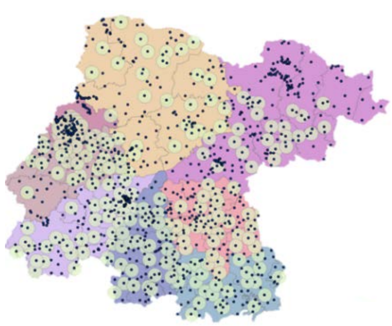
Figure 2. Representation of the Pareto Frontier of region 8.



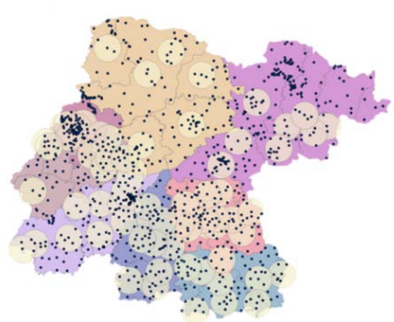
a) Arrangement of PHUs



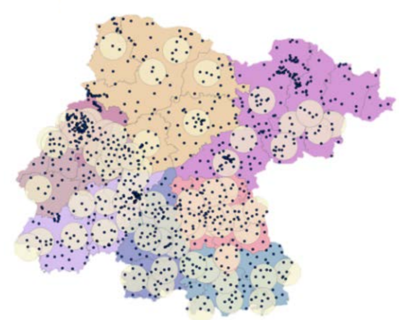
b) Allocation of demand points for the MS



c) Coverage of CS1, CS2, and CS3



d) Coverage of CS4



e) Coverage of CS5

Figure 3. Graphical Representation of the solutions in the state of Guanajuato.

We choose one solution of the Pareto set for each region for the budget B2 to show the graphical representations of the solutions in the eight regions. **Figure 3** illustrates the graphical representation of integrating the solutions of all the regions in a single one. In Figure 3a, the location of all facilities is shown, identifying the existing PHU that remains equal, potential candidate sites with new PHUs, and PHUs that have been upgraded. There are a total of 853 existing PHUs, 486 candidate sites for new PHUs, and 170 PHUs that were upgraded with the budget B2 of each region. The allocation of demand points for the main service is depicted in Figure 3b, with connecting lines and colors representing demand allocation to each PHU, averaging a Euclidian distance of approximately 2.083 km for each assignment across all regions. The coverage of complementary services is displayed in plots **3**c–e. Black points represent demand points and circular shapes represent healthcare units providing the complementary service. Any point covered by the circular shape indicates that the demand point is covered by the service. The results shows that

76% of demand points are covered for CS1, representing 91% of the total demand. It is observed that the same solution was found for CS2 and CS3 due to their identical coverage radius and availability in the same types of facilities. For CS4, there are 96 PHUs with this service, accounting for 9.63% of the total. For CS5, 71% of demand points are covered, representing 85% of the total demand. Overall, these solutions provide short assignment distances for the main service, and the coverage level of complementary services is highly efficient.

5. Conclusions

This article addresses primary healthcare infrastructure planning, focusing on the Mexican healthcare system with a case study applied to the State of Guanajuato, Mexico. It emphasizes the critical need for comprehensive medical service coverage in resource-constrained environments. The bi-objective integer programming model proves effective for data-driven decision-making and resource optimization, validated with real data from Guanajuato, Mexico. The study recognizes the significance of optimizing coverage for complementary services within budgetary constraints. While the primary focus is on the Mexican healthcare system, the methodology demonstrates applicability in similar healthcare systems in developing countries, expanding its reach. Practical and viable solutions in healthcare systems with limited resources are emphasized. Future research could explore alternative multi-objective optimization methods to enhance the Pareto frontier and expand the case study nationwide. Addressing the integration of infrastructure from other public institutions into the planning process stands out as an important aspect for consideration.

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