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Equitable Allocation of Mobile Clinic Services in a Capacity-Constrained Setting

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Abstract. This paper investigates the fair allocation of Mobile Clinic (MC) services in capacity-constrained settings, inspired by the Mexican program *Fomento a la Atenciòn Médica* (FAM). The study proposes and compares two distinct formulations for planning MC operations, focusing on equitable access to healthcare services for marginalized and hard-to-reach populations. The formulations not only determine the MC routes but also introduce a marginalization score to prioritize vulnerable populations. Numerical experiments on synthetic instances allow to compare the computational performance of both formulations. They also reveal the trade-off between maximizing capacity for vulnerable populations and minimizing unused capacity. The findings highlight the challenge of balancing total covered demand with the prioritization of highly vulnerable populations. The paper concludes with recommendations for future research to develop formulations for multiple MCs and to address patient heterogeneity in service times.

Keywords: Mobile Clinics, Humanitarian Logistics, Healthcare Logistics, Operations Research

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1 Introduction

Mobile Clinics (MCs), also known as mobile health units or mobile health clinics, are vehicles that have the purpose of improving access to healthcare by delivering ambulatory services. They transport medical equipment, supplies, and healthcare staff, and have been documented as effective solutions for overcoming access barriers related to factors like time and geography, among others [1]. Their flexibility and versatility make them suitable solutions to provide services in a variety of medical contexts, such as emergency humanitarian activities, vaccination campaigns, or primary care, and this in all planning horizons (short, medium, and long-term).

In the context of humanitarian activities, MCs can provide a range of healthcare services, including but not limited to first aid during disaster relief efforts. In this case, they help diagnose and refer patients to specialized health facilities, ensure follow-up and attend non-emergency patients, and they distribute medicines in remote or difficult access zones [2]. MCs can also support preventive care through outreach supply efforts by, for instance, supplementing the existing vaccine distribution network and increasing immunization rates in the population.

MCs reach remote areas lacking direct or having limited access to healthcare services, ensuring a better coverage. This service differentiates from one-time campaigns because outreach is periodic and repeated at predetermined time periods. These intervals can range from one to six months and are closely related to dosage intervals [3].

MCs also play a crucial role in the health system of developing regions by serving vulnerable communities that are hard-to-reach and/or lack complete or partial access to healthcare services, which is the context of this work. Under this modality, MCs depart from depots in larger cities (which they typically do not serve) and visit nearby communities to provide recurrent or one-time primary care and/or specialized services. At the end of MCs' routes, they return to the depots so the personnel can rest. There are variations of this service. MCs can serve communities during the morning and afternoon, returning to their depot by night [4]. Alternatively, MCs can stay overnight in the communities and return to the depot for consecutive days, such as every weekend [5]. In addition to covering the resting needs of the medical staff, the MC must return to the depot to collect supplies, clinical records, leave samples, among other tasks.

[6] investigated the challenges encountered by healthcare systems that rely on MCs. These challenges include authority-related issues such as constant changes in macro-level medical policies, lack of interest from governments in funding these programs, and insufficient cooperation from healthcare institutions. Additionally, they mention challenges related to inadequate resources or their improper distribution, which can be MCs themselves, medical staff, and medical supplies. They also reported a lack of periodic performance evaluation of these programs. Finally, they pointed out challenges beyond the control of policymakers and medical personal, such as the unwillingness of the population to use the services provided by the MCs. Nevertheless, [6] states that with adequate policies, regulations and planning, time, energy, and resources can be saved or better used.

This paper is inspired by the Mexican program *Fomento a la Atención Médica* (FAM), a major public health initiative in Mexico founded in 2010, focused on delivering primary and specialized healthcare services via MCs. It proposes and compares two distinct formulations to solve the planning of MCs, providing insights into their computational performance and effectiveness. The contributions of these formulations are threefold. First, and contrary to most of the previous papers on MC in which capacity is not considered or it is assumed to be greater than the demand, this paper addresses the more realistic situation where demand is lower than capacity. Moreover, it reckons that populations to serve show different levels of vulnerability in terms of accessibility to basic services, so population in more difficulties should be prioritized. In this setting, the allocation of services to populations using a traditional covered demand maximization objective presents drawbacks, so we propose alternative objective functions to achieve a more equitable access to services. Secondly, the use of such alternative objective functions raises a tradeoff between effectivity and efficiency, because more vulnerable populations are usually further and serving them may introduce, as it will be explained, inefficiencies (i.e., unused capacity). The formulation handles this issue by utilizing "surplus" variables, and demonstrate how bounding these variables leads to different types of solutions. By analyzing the impact of surplus variable constraints, the paper offers valuable managerial insights that can aid in optimizing the deployment and operation of MCs in underserved regions.

The rest of the paper is organized as follows. The next section positions this paper with respect to the existing literature. In Section 3, the problem is formalized and we propose two Mixed-Integer Linear Programming (MILP) formulations that seek to allocate resources fairly by prioritizing the most vulnerable communities. These formulations integrate a refined capacity allocation system quantifying both the unfulfilled demand and the unused capacity. Next, in Section 4, we compare the computational performance of the two formulations using synthetic instances based on real data from the Mexican program FAM, and propose managerial insights on the tradeoff between maximizing the efficiency of the solutions and their effectiveness. Section 5 presents our conclusions and proposes future lines of research.

2 Literature review

When examining the literature on MC logistics, we identify two distinct service modalities that are not formally classified. These modalities differ based on whether trips are planned daily, allowing for visits to multiple localities within a single day, or whether trips span multiple days, requiring an MC to remain in a single locality for at least one day.

Papers in the first modality, which allow multiple stops in different localities on a single day, are commonly modeled as variants of the Vehicle Routing Problem (VRP). This type of problems work under the assumption that travel times between localities, along with the time required for dismantling and setting up the MCs, are not important, so the MC's capacity to serve patients is not significantly affected by these activities [3, 4, 7–10]. We will refer to this type of problems as *multiple-stops per day* problems.

Conversely, when travel times between localities are substantial, relocating during working hours diminishes the time that MCs can allocate to patient care. This modality, predominantly observed when MCs operate in extensive and remote regions with particularly challenging routes, involves MCs staying in a locality for one or several full days, with inter-locality travel occurring after working hours. This paper specifically addresses these types of issues, which will be referred to as *full-day stop* problems.

The remainder of this section exclusively examines papers pertaining to *full-day stop* problems, which are the most pertinent to our case. Various facets of these problems, including operational aspects (routing) and tactical decisions (capacity allocation), are reviewed. Additionally, this section explores how fairness in service access has been addressed within the logistics literature of MCs.

Routing problems involve planning vehicle routes by selecting customers to visit, determining the sequence of visits, and scheduling the timing of each visit. The most basic version of a routing problem in MCs entails deciding which demand points to visit and determining the sequence of these visits.

To the best of our knowledge, [11] was the first to address an MC problem as an optimization problem, specifically as a Covering Tour Problem (CTP), a variant of location-routing problems. This problem involves covering a subset of nodes in a graph. The objective is to find the shortest route that covers the entirety of demand in the graph, with each visited node capable of covering the demand of other nodes within a predetermined distance [12]. In [11] CTP, population centers to be visited are selected within a network representing a developing region with accessibility issues.

In routing problems, the predominant objective is the minimization of travel costs or distance [11, 13, 14]. [13] dealt with a dynamic demand problem arising in the context of humanitarian logistics, where refugee groups cross borders on their journey, and by doing so, they enter and exit the network at different periods. In particular, a route across 21 city centers is used to model the pathway followed by refugees during the Honduras migration crisis in 2022. In the health services context, [14] modeled and solved a problem where MCs are used to deliver dental and ophthalmology services to remote populations, establishing routes that were repeated every two weeks to serve the customers of a for-profit company in Istanbul. [15]

addressed the planning of a MC trips offering dental services over a planning horizon of 26 weeks in rural Southwest, Montana.

In the context of MCs, demand satisfaction or *coverage* decisions, are linked to the number of patients attended during each stop of a MC in a locality. [11, 13] assumed that once a locality has been visited in the planning horizon, it has been covered (i.e., all its demand has been satisfied). [15] assumes that the MC can visit one locality per trip, but it can stay multiple days (and overnights) in order to fully satisfy the locality's demand. On the other hand, [2] determines the number of days the MC must stay in a locality, assuming a maximum number of patients can be attended per day. [14] considered full or partial coverage (i.e., demand satisfaction) of the localities based on their distance from the MC stop.

Indeed, we observed that most studies assume an uncapacitated setting or, if capacitated, require the capacity to be greater than the demand to ensure feasible solutions. When the service capacity is lower than the total demand, the maximization of the actual served demand, or the portion of the served demand relative to the total demand at each locality becomes relevant. In such cases, the primary objective shifts to the minimization of unmet demand, as in [2].

Within the context of MCs, capacity is associated to the available time to attend to patients, which can be allocated to visited localities. Capacity allocation has been considered as a problem on its own in [15], where the frequency of MC stops at each location over the planning horizon needs to be determined assuming that a fixed number of patients can be attended to during a day. Other studies have approached capacity as a strategic decision by deciding whether or not a MC is used within the planning horizon. This becomes especially relevant designing MC systems, so that costs associated with the deployment of a MC (e.g., acquisition or assignment of medical staff), are considered in addition to traveling costs [2, 13]. [14] explored various capacity sizes, defining capacity as the product of the number of days in the planning horizon and by the size of the fleet. Subsequently, they selected the solution that provided the largest coverage while minimizing weighted costs.

[15] estimates capacity as the total number of patients that can be treated per workday in a locality, and then the number of workdays allocated to each locality is determined. However, there is a working time limit within the planning horizon, which must be large enough for a feasible solution to exist, considering how the model was formulated.

[2] is to our knowledge the only work that considers a fixed-capacity setting with the possibility of unfulfilled demand in a *full-day stop* problem. However, it does not handle unused capacity, or in other words, what happens when an MC serves a locality whose demand is smaller than the MC's capacity. Recall that, since this is a *full-day stop* problem, the MC can visit only one locality per day.

In conclusion, none of the previous works modeled a link between the time spent in a locality and the number of patients served. While this is a convenient simplification of the problem, it does not guarantee an efficient and adequate use of medical staff time. Additionally, they did not suggest any mechanism to track or identify blind spots for unused capacity. In our case, the demand significantly exceeds the capacity, raising a new question on how to choose the localities that will be served and those that will not. Our objective is not to minimize costs, but to ensure fair access to services.

In this regard, all the works we reviewed, except for [14], considered all patients as having the same priority. Therefore, patients contribute equally to the objective function when maximizing the covered demand. However, in our case, different levels of patient marginalization impact patients' priority, which needs to be taken into account when deciding access to services. To our knowledge, [14] is the only work considering fairness when planning MC services. In their approach, localities can be fully or partially covered, depending on their proximity to a MC. Based on the locality's coverage, a "fairness score" is considered fully or partially in the objective function, which seeks to maximize this fairness score. Fairness is thus related to the locality's distance to the service, rather than to the characteristics of the locality (e.g., available infrastructure).

Table 1 summarizes the main features of the reviewed papers dealing with *full-day stop* problems. It can be observed that our work differs from previous ones in several aspects. In addition to routing and capacity allocation decisions, we explicitly consider unmet demand and unused capacity decisions to provide more control over the allocation of MCs' service time. Moreover, unlike most previous works, demand exceeds capacity, making the traditional objective of maximizing covered demand unsuitable for our case. For this reason, our study seeks to plan the use of MCs' capacity in such a way that population access to services is granted in a fair manner that takes into account the priority or needs of the localities.

3 Problem modeling and mathematical formulations

In this section, we introduce the planning of healthcare service delivery using MCs in a regional setting and propose two formulations to address this issue. The objective is to plan a fixed number of trips for each MC, prioritizing the most vulnerable localities while minimizing the traveled distance. In the following, we describe the characteristics of the studied context and then present the two formulations.

Without loss of generality, we assume a region containing several sparsely populated localities that are difficult to reach due to their lack of access to main roads. These localities endure compromised living conditions and lack access to essential services such as transportation, healthcare, sanitation, and education, among others. However, the levels of vulnerability among these localities are not homogeneous, as some are more marginalized (i.e., have lower access to services) than others. Given the absence of health infrastructure in these localities, MCs emerge as a viable, if not the only, alternative to provide healthcare to these populations. It should be noted that only a portion of the total population in these localities requires scheduling a medical appointment, and we assume that the demand for services is deterministic and known. Furthermore, we assume that all patients require a uniform average consultation time, thus the number of patients that can be served by a MC per day remains constant.

MCs deliver primary and some specialized care through service trips during which they visit multiple localities. Each trip begins with a MC departing from an origin depot, following a sequence of localities to visit, and concluding at said depot. Depots are community-owned facilities that serve as operational centers and storage sites for essential medical supplies, drugs, and clinical records. Each MC is staffed by medical professionals and a designated driver, who can work for a limited number of consecutive days before requiring a resting period, thus limiting the duration of each trip. Considering the resting needs of the medical staff between trips, depots also function as resting points for MCs and their staff during rest days. Depots are situated in nearby urbanized localities, referred to as *primary localities*, which are not required to be served.

Within a service trip, a MC can serve the same locality for consecutive days or travel to a different locality between each service day. The localities to be visited are referred to as *secondary localities*. Due to long set-up and travel times, a MC can serve at most one locality per day. *Secondary localities* also act as service hubs for the population of nearby localities that are not visited, referred to as *satellites*. A *satellite locality* can be assigned to a *secondary locality* if their distance is within a reasonable limit. In this case, the population of the *satellite locality* requiring medical attention travels to and receives service from the MC visiting the *secondary locality*.

It should be noted that the demand exceeds the capacity. Therefore, while efficient resource utilization is aimed for, adjustments must be made to prioritize localities with high levels of marginalization.

As explained before, our problem falls into the category of *full-day stop* problems, where MCs can only visit one locality per day. We found that there have been two ways of formulating this type of problem. The first formulation, which we will refer to as the *day-based* formulation, follows the approach in [2], [13] and [14], and considers the problem as a multi-period one where it needs to be decided which locality to visit each period in the planning horizon.

Alternatively, the second formulation, which will be referred to as the *trip-based* formulation, inspired by [11] and [15], does not decide specifically which localities to visit each day, but how many days are assigned to each locality on every trip and the sequencing of visits, which usually coincides with a working week.

In the following, we adapt these approaches to develop two formulations for our case study. Our objective with both approaches is to compare

Study	Services	Objective Function	Decisions	Capacity Assumptions	Data
[2]	DR	Min C and UD	R, Act, Cov, UD	Cap	Jakarta flood
[11]	PR	Min C and #S, Max Cov	R	UCap	Hard-to reach populations in Suhum District, Ghana
[13]	PR	Min C	R, Act	UCap	Honduras migration crisis
[15]	DS	Max Cov	All, Cov	Cap	Rural populations in Southwest Montana
[14]	DS and Oph	Max FS, Min Dist	R, Cov, FS	Cap	Crowded district in Istanbul, Turkey
This paper	PR	Max FS, Min Dist	R, All, UD, S	Cap	Marginalized communities in Mexico

Table 1 Related works

(DR=Disaster Relief, PR=Primary Care, DS=Dental Services, Oph=Ophthalmology Services, C=Costs, UD=Unfulfilled Demand, #S=Number of Stops, Cov=Coverage, FS=Fairness Score, Dist=Distance Travelled, R=Routing, Act=Activation, All=Allocation, S=Surplus, UCap=Uncapacitated, Cap=Capacitated)

their computational performance and determine which one is better suited to the context of our problem for further analysis. In addition, alternative objective functions are proposed to achieve fairer access to services based on the marginalization levels of localities. Lastly, a lexicographic optimization method is presented to include, as a secondary objective, the minimization of the distance traveled by the MC.

3.1 Day-based formulation

In a region composed by $|L|$ localities, each locality $i \in L$ has a demand d_i to be fulfilled, which is an estimate of the fractional number of days that would take a MC to attend all the patients in a locality. There are $|T|$ days in the planning horizon and the MC can only visit one locality per day $t \in T$. However, the staff of the MC works in periods of five consecutive days and rest the following two. Therefore, in days $T_w \subseteq T$ the MC must start its working period departing from the *primary locality*. Analogously, the MC must return to the *primary locality* in days $t \in T_w + N$, at the end of every period of N consecutive working days. The *primary locality* will be referred to in the model as $i = 1$ or $i = 2$. Declaring the days when the MC needs to return to and depart from the *primary locality* in the form of subsets is practical, as these days are predetermined. The medical staff adheres to a strict working calendar year by law, which designates weekends as their days off and also includes holidays.

The MC can only perform $|T| - |T_w + N|$ one-day visits. However, as mentioned previously, there is a way to serve the demand of a locality without directly visiting it. If locality j can be reached from locality i by walking a distance τ (i.e., $b_{ij} \leq \tau$, with b_{ij} being the distance between i and j), then locality i can absorb the demand of locality j. In other words, the population from locality j can walk to locality i to benefit from the services of the MC if it visits locality i. Locality j, whose demand has been absorbed by another locality, will be referred to as a *satellite locality*, and locality i, that will be visited by the MC, will be referred to as a *secondary locality*. This is mathematically modeled by assignment variables a_{ij}, which take the value 1 to indicate that locality i is a *satellite* and its demand is absorbed by *secondary locality* j. Furthermore, if $a_{ii} = 1$, then locality i is a *secondary locality*. When a locality is neither assigned to another nor assigned to itself, it means that it will remain unvisited.

Next, the integer allocation of one-day visits to *secondary localities* is modeled by integer variables x_i, which represent the number of one-day visits to locality i. It is important to note that multiple visits may not occur consecutively, although they do when the formulation prioritizes the minimization of distance. In the context of this study, traveling between localities does not compromise capacity, as it is conducted during non-working hours. These trips are scheduled after the MC closes (usually at 4 pm), allowing sufficient time to arrive at and be ready to serve the next locality by early morning the following day.

As previously pointed out, the demand d_i is a fractional value representing the amount of medical attention requested by the population of locality i over the planning horizon, measured in days. Considering that the decision variable x_i allocates one-day visits, allocating visits to a demand point often results in either a portion of unmet demand if the allocated capacity is less than the demand, or surplus (unused capacity) if the allocated capacity exceeds the demand. Hence, additional decisions in the problem include addressing the unmet demand in a locality, denoted as p_i, or the surplus allocated to a locality denoted as p'_i.

Additionally, it is possible that not all the one-day visits x_i allocated to locality i are solely intended to meet the demand of said locality but also the demand of other *satellite localities* j assigned to it. Therefore, variable e_{ij} tracks the capacity allocated to a *satellite locality* i but supplied in *secondary locality* j. However, when $i = j$, e_{ij} also tracks the capacity allocated to and supplied in *secondary locality* i.

Finally, decision variable y_{ijt} helps set the sequence of visited localities and the corresponding days (i.e., the MC's route) as follows: when locality j is visited on day t after visiting locality i the day before, then y_{ijt} is set to 1. Note that $y_{iit} = 1$ indicates that the same locality i is visited on consecutive days $t-1$ and t, or in other words, that the MC stays at i for both days.

Tables 2 and 3 present the parameters, sets, and decision variables for the *Day-based model*, followed by its formulation.

Objective Function:

$$\max \sum_{j \in L} \left(\sum_{i \in L:(i,j) \in A} e_{ji} - p'_j \right) \tag{1}$$

Subject to:

$$\sum_{i \in L:(i,j) \in A} e_{ji} = d_j - p_j + p'_j \quad \forall j \in L \tag{2}$$

$$p_i \leq d_i \quad \forall i \in L \tag{3}$$

$$a_{ji} \leq M e_{ji} \quad \forall (i,j) \in A \tag{4}$$

$$e_{ji} \leq M a_{ji} \quad \forall (i,j) \in A \tag{5}$$

$$\sum_{j \in L:(i,j) \in A} e_{ji} = x_i \quad \forall i \in L \tag{6}$$

$$\sum_{i \in L:(i,j) \in A} a_{ji} \leq 1 \quad \forall j \in L \tag{7}$$

$$\sum_{i \in L'} \sum_{t \in T} y_{ijt} \leq M \sum_{\substack{i \in L:(i,j) \in A \\ i = j}} a_{ji} \quad \forall j \in L \tag{8}$$

$$\sum_{\substack{i \in L \\ (i,j) \in A \\ i = j}} a_{ji} \leq \sum_{i \in L'} \sum_{t \in T} y_{ijt} \quad \forall j \in L \tag{9}$$

$$\sum_{i \in L'} \sum_{t \in T} y_{ijt} = x_j \quad \forall j \in L \tag{10}$$

$$\sum_{i \in L'} y_{ijt} = \sum_{i \in L'} y_{ji(t+1)} \quad \forall j \in L', \, t \in \{1, \ldots, |T|-1\} \tag{11}$$

$$\sum_{j \in L} y_{1jt} = 1 \quad \forall t \in T_w \tag{12}$$

$$\sum_{i \in L} y_{i1(t+N)} = 1 \quad \forall t \in T_w \tag{13}$$

$$\sum_{i \in L'} \sum_{j \in L'} y_{ijt} = 1 \quad \forall t \in T \tag{14}$$

$$y_{ijt}, \, a_{ji} \in \{0,1\} \quad \forall i,j \in L, \, t \in T \tag{15}$$

$$x_i \in \mathbb{Z}^+ \quad \forall i \in L \tag{16}$$

$$e_{ji}, \, p_i, \, p'_i \geq 0 \quad \forall i,j \in L \tag{17}$$

Objective function (1) maximizes the total covered demand which is calculated by subtracting the surplus from the allocated capacity of every locality j.

	Parameters
d_i	Demand of locality i (in days)
b_{ij}	Distance between localities i and j
N	Number of consecutive working days before resting
	Sets
L'	Set of localities (including the *primary locality*)
$L \subseteq L'$	Set of localities excluding the *primary locality*
A	Pairs of localities that can be assigned to each other ($A = (i, j) : i, j \in V : b_{ij} \leq \tau$)
T	Days in the planning horizon ($T = \{1, ...t, ...\|T\|\}$)
$T_w \subseteq T$	Set of days when MC departs from the *primary locality*

Table 2 Parameters and Sets of the *Day-based model*

a_{ji}	Takes value 1 if locality j is assigned to locality i; 0 otherwise
x_i	Number of days locality i will be visited by the MC during the planning horizon
e_{ji}	Capacity allocated to locality j served in locality i
y_{ijt}	Takes value 1 if MC visits locality j in day t after visiting locality i in day $(t-1)$; 0 otherwise
p_i	Unmet demand at locality i
p'_i	Surplus (unused capacity) at locality i

Table 3 Decision Variables of the *Day-based model*

Constraints (2) state that the capacity allocated to a locality j to be covered in other locality i must be equal to the demand of said locality j minus its unmet demand plus its surplus. Additionally, constraints (3) ensure that the calculated unmet demand does not exceed the demand.

Constraints (4) and (5) enforce that if capacity is allocated to a locality j and served in a locality i, then locality j must be assigned to locality i. Constraints (6) ensure that the capacity allocated to any locality i visited by the MC, is an integer number of days. Constraints (7) guarantee that a locality j falls into one of three following scenarios: it can be included in the route by setting a_{ji} to 1 when $i = j$, assigned to another locality i when a_{ji} is set to 1 but $i \neq j$, or it can remain unvisited by setting a_{ji} to 0 for all i. Constraints (8) and (9) enforce that if a locality j is in the MC's route, then a_{ji} must be equal to 1 when $i = j$. Similarly, they ensure that when a locality j is assigned to itself, indicating that it is a *secondary locality*, it must be part of the route.

Constraints (10) to (14) address the routing aspect of the problem. Constraints (10) link the capacity allocation and routing decision variables by ensuring that every locality on the route must be visited the exact number of days specified by x_i. Constraints (12) and (13) guarantee that the MC begins and ends every trip at the *primary locality* ($i = 1$) on the days specified in the subsets T_w and $T_w + N$. Constraints (11) maintain the continuity of the route and constraints (14) ensures that the MC visits only one locality per day. Finally, constraints (15) to (17) describe the nature of the decision variables.

3.2 Trip-based Model

As mentioned before, it is also possible to approach the MC planning problem as a sequencing problem. In this approach, a solution is sought for each set of consecutive working days that begin and end in the *primary locality*, referred to as trips $c \in C$.

Therefore, the decision-making process revolves around determining how many consecutive days each locality will be visited during each trip. To this end, we introduce three new sets of decision variables. Variables x_{ic} set the number of days the MC visits a locality i in trip c. Variables e_{jic} give the capacity allocated to a locality j served in locality i in trip c. Variables y_{ijc} take the value 1 if the MC visits locality j after visiting locality i in trip c, and 0 otherwise.

Decision variables a_{ji}, p_i and, p'_i remain unchanged, as well as the parameters already defined d_i and b_{ij}. The *Trip-based* formulation can be stated as follows:

Objective Function:

$$\max \sum_{j \in L} \left(\sum_{c \in C} \sum_{i \in L:(i,j) \in A} e_{jic} - p'_j \right) \tag{18}$$

Subject to:

$$\sum_{c \in C} \sum_{i \in L:(i,j) \in A} e_{jic} = d_j - p_j + p'_j \quad \forall j \in L \tag{19}$$

$$p_i \leq d_i \quad \forall i \in L \tag{20}$$

$$a_{ji} \leq M \sum_{c \in C} e_{jic} \quad \forall (i,j) \in A \tag{21}$$

$$\sum_{c \in C} e_{jic} \leq M a_{ji} \quad \forall (i,j) \in A \tag{22}$$

$$\sum_{j \in L:(i,j) \in A} e_{jic} = x_{ic} \quad \forall i \in L,\, c \in C \tag{23}$$

$$\sum_{i \in L:(i,j) \in A} a_{ji} \leq 1 \quad \forall j \in L \tag{24}$$

$$\sum_{i \in L'} \sum_{c \in C} y_{ijc} \leq M \sum_{\substack{i \in L:(i,j) \in A \\ i=j}} a_{ji} \quad \forall j \in L \tag{25}$$

$$\sum_{\substack{i \in L:(i,j) \in A \\ i=j}} a_{ji} \leq \sum_{i \in L'} \sum_{c \in C} y_{ijc} \quad \forall j \in L \tag{26}$$

$$\sum_{i \in L} x_{ic} = f_c \quad \forall c \in C \tag{27}$$

$$\sum_{i \in L'} y_{ijc} = \sum_{i \in L'} y_{jic} \quad \forall j \in L,\, c \in C \tag{28}$$

$$\sum_{j \in L} y_{1jc} = 1 \quad \forall c \in C \tag{29}$$

$$\sum_{i \in L} y_{i2c} = 1 \quad \forall c \in C \tag{30}$$

$$\sum_{i \in L'} y_{ijc} \leq x_{jc} \quad \forall j \in L,\, c \in C \tag{31}$$

$$x_{jc} \leq M \sum_{i \in L'} y_{ijc} \quad \forall j \in L,\, c \in C \tag{32}$$

$$\sum_{i \in L'} y_{ijc} \leq 1 \quad \forall j \in L',\, c \in C \tag{33}$$

$$\sum_{j \in L'} y_{ijc} \leq 1 \quad \forall i \in L',\, c \in C \tag{34}$$

$$\sum_{(i,j) \in S} y_{ijc} \leq |S| - 1 \quad \forall c \in C \tag{35}$$

$$y_{ijc}, a_{ji} \in \{0,1\} \quad \forall i,j \in L,\, c \in C \tag{36}$$

$$x_{ic} \in \mathbb{Z}^+ \quad \forall i \in L,\, c \in C \tag{37}$$

$$e_{jic},\, p_i,\, p'_i \geq 0 \quad \forall i,j \in L,\, c \in C \tag{38}$$

Equations (18) to (26) are equivalent to (1) to (9) in the *day-based* formulation, but include slight modifications to operate within a framework based on trips. Indeed, the main difference between the two formulations lies on how the routing of the MC is structured. In the case of the *trip-based model*, constraints (27) to (35) address the routing aspect of the problem. This formulation introduces a new parameter f_c which sets in constraints (27) the number of days for each trip to exactly f_c. Constraints (28) take care of the continuity of the route, and constraints (29) and (30) guarantee that every trip of the MC begins and concludes in the *primary locality*. Specifically, when $i = 1$, it designates the *primary locality* as the departure point, and when $i = 2$, it designates the *primary locality* as the arrival point. Constraints (31) and (32) enforce that when capacity has been allocated to a locality j, it must be visited by the MC and vice versa. Constraints (33) and (34) ensure that throughout every part of the MC route, the MC arrives from only one locality and arrives at only one locality. This formulation deals with subtours $(i,j) \in S$, hence subtour elimination constraints are introduced in equations (35). Finally, constraints (36) to (38) describe the nature of the decision variables.

3.3 Alternative objective functions

As explained above, the main objective when planning the MC activity is to provide care to the population that needs it most. We introduce a new parameter m_j which quantifies how marginalized a locality j is, thus indicating the urgency of fulfilling its demand compared to other localities.

Accordingly, we propose alternative objective functions to maximize the satisfied demand weighted by its marginalization factor m_j. In the proposed objective functions, the parameter m_j acts as a reward, which is obtained according to the demand covered in the locality j. Objective functions (39) and (40) correspond to the *day-based* and *trip-based* formulations, respectively.

$$\max \sum_{j \in L} m_j \left(\frac{\sum_{i \in L:(i,j) \in A} e_{ji} - p'_j}{d_j} \right) \tag{39}$$

$$\max \sum_{j \in L} m_j \left(\frac{\sum_{c \in C} \sum_{i \in L:(i,j) \in A} e_{jic} - p'_j}{d_j} \right) \tag{40}$$

However, focusing solely on the maximization of the covered weighted demand might lead to an inefficient usage of the MC's capacity. To overcome this issue, we propose to consider, as secondary objective, to minimize the total distance traveled by the MC. Considering the clear hierarchy between the two objectives, we developed a lexicographic optimization approach.

3.4 A lexicographic optimization method for planning MC's activities

Multi-objective optimization addresses problems involving two or more objective functions to be optimized simultaneously. In some cases, the decision-maker's preferences regarding each objective are clearly hierarchical, allowing the possible solutions to be ranked in a lexicographic order based on their objective function values. The strong hierarchy between the two objectives considered when planning the MC's activities (i.e., maximizing the covered weighted demand and minimizing the traveled distance) led us to choose a lexicographic optimization approach rather than a more traditional method, in which the two objectives would be influenced by user-defined weights and combined into a single, yet heterogeneous objective function.

To this end, a sequential, two-step algorithm is proposed. In the first step, the problem is solved for the primary objective (i.e., maximization of the covered weighted demand) yielding z^1, the maximum feasible value of the primary objective. In the second step, the problem is solved again, but this time using the secondary objective (i.e., minimization of the distance traveled by the MC) subject to the additional constraint that the value for the primary objective must be at least equal to $z^1 - \epsilon$, where $\epsilon \geq 0$ is a parameter quantifying the deterioration that the decision maker is willing to accept on the primary objective in order to optimize the secondary one. In our context, the second step is always feasible and results in z^2, the shortest route value for the MC that ensures a covered weighted demand of at least $z^1 - \epsilon$.

The total distance traveled by the MC can be computed by equations (41) and (42) for the *day-based* and the *trip-based* formulations, respectively.

$$\min \sum_{i \in L'} \sum_{j \in L'} \sum_{t \in T} b_{ij} y_{ijt} \tag{41}$$

$$\min \sum_{i \in L'} \sum_{j \in L'} \sum_{c \in C} b_{ij} y_{ijc} \tag{42}$$

Also, equations (42) and (44) state the additional constraints on the value for the primary objective to be introduced in the second step for the *day-based* and the *trip-based* formulations.

$$\sum_{j \in L} \left(\sum_{i \in L:(i,j) \in A} e_{ji} - p'_j \right) \geq z^1 - \epsilon \tag{43}$$

$$\sum_{j \in L} \left(\sum_{c \in C} \sum_{i \in L:(i,j) \in A} e_{jic} - p'_j \right) \geq z^1 - \epsilon \tag{44}$$

Finally, lexicographic algorithms for the *day-based* and the *trip-based* formulations are :

Lexicographic algorithm for the day-based formulation:

- z^1 = Solve (39), (2)-(17)
- z^2 = Solve (41), (2)-(17), (43)

Lexicographic algorithm for the trip-based formulation:

- z^1 = Solve (40), (19)-(38)
- z^2 = Solve (42), (19)-(38), (44)

4 Computational Results

This section aims to evaluate the computational performance of the proposed formulations and to elucidate the behavior of the objective functions designed to ensure equitable access to the services provided by the MC. To this end, numerical experiments were conducted on a set of synthetic instances inspired by the Mexican program *Fomento a la Atención Médica* (FAM), a major public health initiative in Mexico founded in 2010, focused on delivering primary and specialized healthcare services via MCs. Initially, FAM targeted 20,000 localities with around 3.9 million people nationwide. These localities have populations of less than 2,500 individuals and face healthcare access challenges due to their location, insufficient infrastructure, and/or limited technological and human resources for providing ongoing care to their residents.

The section is organized into three parts. First, a comprehensive description of the instance generation process is provided. Next, the results produced by the two formulations are presented, and their computational performance is compared. Finally, managerial insights are derived from an in-depth analysis of how limiting the surplus through variables p'_j in the proposed formulations impacts the structure of the produced solutions.

4.1 Instances generation

We utilized public data from FAM to generate a set of instances that allow us to test the performance of the proposed methods and their ability to support FAM's managers in their decision-making processes. As previously mentioned, FAM is a major public health initiative in Mexico, focused on delivering primary and specialized healthcare services to vulnerable populations via MCs. Although most of the regions where the FAM program has been deployed cover large areas with total populations that would require two, three, and up to ten MCs to satisfy their demand, the formulations we presented only envisage the planning of activities for a single MC. However, one of the first decisions made by FAM managers involves partitioning the area to serve into sub-regions, each centered around a *primary locality* to which a single MC is assigned. Therefore, the proposed formulations are intended to assist managers in organizing the activities of each individual MC they oversee.

The capacity of a MC was estimated based on the length of the considered planning horizon (four weeks). Thus, for the *day-based* model, $|T| = 24$, $T_w = \{1, 7, 13, 19\}$ and $N = 5$, whereas for the *trip-based* model, $|C| = 4$ and $f_c = 5 \quad \forall c \in C$. Since a MC can visit only one locality per day, up to 20 localities can be visited during the planning horizon. We assume that during each of the 20 working days, the MC's medical staff (comprising two teams) works a 8-hour shift, totaling 320 hours of available service time. Assuming an average service time of 15 minutes per patient, we estimate that an MC is able to serve an average of 64 patients daily.

In addition to a designated *primary locality*, each sub-region includes several localities of varying sizes and vulnerabilities. After analyzing the available data [16], we observed that smaller localities are more common and exhibit higher marginalization than larger localities. To capture this pattern in our instances, we considered instances with $|L| = 25$ and $|L| = 50$ localities, and categorized the localities into three types: *small*, *medium*, and *large*, so that $L = L_x \cup L_m \cup L_l$. We set the number of *small*, *medium*, and *large* localities to 70%, 25%, and 5% of $|L|$, respectively.

To construct the set of numerical instances, we used data from FAM's operations in Aguascalientes and Chihuahua, Mexico [16]. In the context of the FAM program, Aguascalientes is among the states with the highest average demand per locality, while Chihuahua is among those with the lowest.

One sub-region covered by a single MC in each of Aguascalientes and Chihuahua states was arbitrarily selected, and the following procedure was applied: the population of each locality within the selected sub-regions was obtained, multiplied by 0.246 [17], then by 15 minutes, and finally converted from minutes to days to estimate the demand for healthcare services. The average demand and standard deviation were calculated for each sub-region. The values obtained from

Aguascalientes were used to represent the demand of *small* localities (μ_x^d, σ_x^d), while those from Chihuahua represented the demand of *large* localities (μ_l^d, σ_l^d). For the medium sized localities, the average and standard deviation were calculated based on the combined data from both sub-regions and used to represent their demand (μ_m^d, σ_m^d).

The marginalization scores used were inspired by the marginalization index (MI) calculated by the Mexican government to categorize areas based on their degree of socioeconomic disadvantage. The Mexican MI incorporates factors such as access to education, health services, living conditions, and sanitation, with higher values indicating greater marginalization.

The MIs of the localities in the previously referenced sub-regions of Aguascalientes and Chihuahua were retrieved, and the average and standard deviation were calculated for each sub-region. The values obtained from Aguascalientes MIs were used to represent the marginalization score of *small* localities (μ_x^{MI}, σ_x^{MI}), while those from Chihuahua represented the marginalization score of *large* localities (μ_l^{MI}, σ_l^{MI}). For the medium sized localities, the average and standard deviation were calculated based on the combined data from both sub-regions, and used to represent their marginalization score (μ_m^{MI}, σ_m^{MI}).

This process led to the numerical values reported in Table 4.

We assumed that the demand and MI for each group of localities follows a normal distribution and for each locality j in each instance, we sampled the corresponding μ^d and σ^d, and μ^{MI} and σ^{MI} to produce the locality demand d_j and marginalization score m_j. However, we ensured that the demand in each instance exceeded the capacity of an MC. Specifically, we considered two scenarios where the total demand reached at least 120% and 150% of a MC's capacity, respectively. To achieve this, we repeated the sampling process until the specified demand-to-capacity ratio was satisfied.

Finally, we also considered the geographical distribution of the localities. After analyzing the available data, we identified two main patterns: one where localities appear dispersed *randomly*, and another referred to as *centralized*, where *large* and *medium* localities occupy the center of the territory and are surrounded by smaller, more marginalized localities. Thus, we considered two alternative scenarios for the distribution of localities: one with a *random* geographical distribution and one with a *centralized* distribution.

To generate the numerical instances, we once again used data from the state of Aguascalientes, Mexico. Initially, we considered a rectangle of size (R_x, R_y) enclosing the previous referenced sub-region as the basic area to locate random generated localities. For a *random* geographical distribution, localities' coordinates were generated within the basic area by sampling from a uniform distribution. For instances with a *centralized* geographical pattern, the coordinates α_x, α_y of *large* localities were generated by sampling a uniform distribution such that $\alpha_x = R_x U(0.0001; 0.05)$ and $\alpha_y = R_y U(0.0001; 0.05)$ from the center of the basic area. Coordinates of *medium* and *small* localities were produced similarly, but sampled within uniform intervals [0.05-0.2] and [0.2-0.5] from the basic area's center. Finally, distances b_{ij} between each pair of localities i and j were calculated from their coordinates using the haversine formula and multiplied by a coefficient of 1.5 to account for road distance, and a value of 5 *km* for τ was considered.

By combining the number of localities ($|L| = 20, 50$) and the two possible geographical distribution patterns (random and centralized), four types of instances were created. For each type, ten replicas were generated as described previously, resulting in a total of 40 instances. Table 5 presents the main characteristics of the proposed instances.

Figures 1(a) to 1(d) illustrate the position of the localities in the first instance of Types A to D, respectively. The *primary locality* is denoted by a purple star, whilst the *large*, *medium*, and *small* localities are represented by yellow, green, and red dots, respectively.

4.2 Numerical Results

To compare the computational performance of the *day-based* and *trip-based* models, the 40 instances presented in Section 4.1 were solved using the lexicographic method described in Section 3.4. Firstly, the covered demand was maximized and then the distance travelled by the MC was minimized. The instances were solved using commercial solver Gurobi on one of the Digital Alliance of Canada's servers. Each task was allocated one CPU and 32

	Small		Medium		Large	
	μ_x^-	σ_x^-	μ_m^-	σ_m^-	μ_l^-	σ_l^-
Demand	0.13	0.12	0.56	0.67	1.79	0.94
Marginalization Index (MI)	23.17	0.59	20.24	3.05	18.22	2.33

Table 4 Parameters used for the generation of d_i and m_j for the different instances, assuming they follow normal distribution $N(\mu_-^-, \sigma_-^-)$

Type	No. of Localities	Geographical Distribution	Demand/Capacity Ratio	No. of Small-Medium-Large Localities
A	25	Random	≥ 1.2	17, 5, 3
B	25	Centralized	≥ 1.2	17, 5, 3
C	50	Random	≥ 1.5	34, 10, 6
D	50	Centralized	≥ 1.5	34, 10, 6

Table 5 Types of instances considered for the computational experiments

GB of memory. The optimality GAP was set to 0.001, and the solving time was limited to five and ten hours (i.e., 18000 and 36000 seconds) for the first and second stages of the lexicographic algorithm. The results are shown in Table 6 which reports for the *Day-based* and *Trip-based* formulations: the optimality gap reached at the end of the first and second stages of the lexicographic algorithm (columns Gap_1 and Gap_2, respectively), as well as the associated computational times in seconds (T_1 and T_2, respectively).

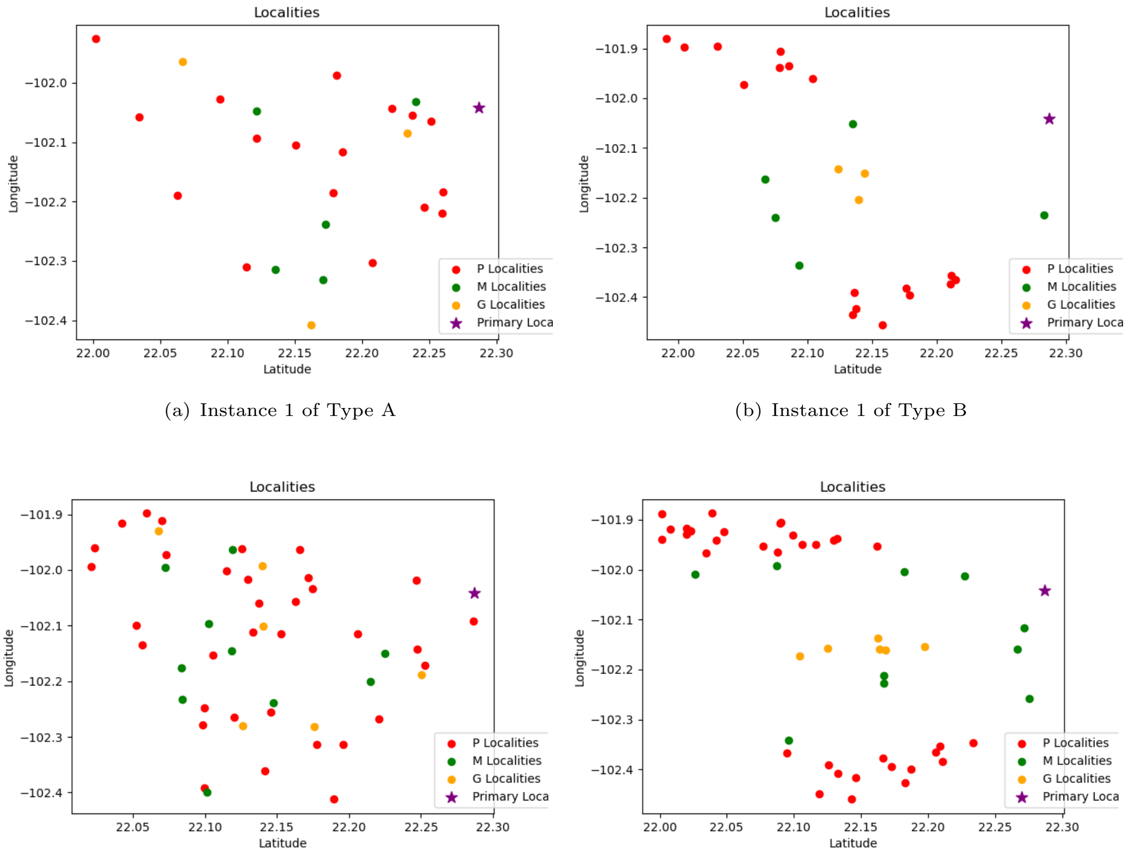
If we consider the first stage of the lexicographic algorithm (i.e., the maximization of the weighted demand covered), Table 6 shows that both formulations solved to optimality all the instances (recall that the optimality gap was set to 0.1%), although the *trip-based* formulation was unable to reduce the gap under 0.5% for instance 24. That said, both formulations seems quite efficient, solving most of the instances in only a few seconds, although for seven specific instances the *trip-based* formulation required more than 100 seconds. However, when looking at the second stage of the lexicographic algorithm, the formulations showed very different performance. Indeed, the *day-based* formulation was able to solve to optimallity all the instances, requiring computational times ranging from only 11 seconds up to 22419 seconds, although 27 out of the 40 instances were solved in less than five minutes. The *trip-based* formulation only produced optimal solutions in eight instances out of 40, and for the 32 instances for which the proof of optimality was not reached, optimality gap was always over 10%.

Unsuprisingly, instances A and B seem easier to solve, requiring computational times slightly lower than instances C and D. In fact, even the *trip-based* formulation was able to produce optimal solutions for eight out of 20 instances in these groups. Group C seems to be the most difficult for both formulations, although the variability in the computational times make difficult to draw clear conclusions.

To summarize, the *day-based* formulation exhibited better performance, solving for all the cases the two stages of the lexicographic algorithm to optimality, and doing so in reasonable computational times. The *trip-based* formulation clearly struggled with the second stage of the lexicographic algorithm, and after exhausting the 10 hours of computational time, produced an average gap of 22.84%. Given its better performance, the rest of our experiments will be conducted using only of the *day-based* formulation.

4.3 Managerial insights

As it has been previously pointed out, the MC's literature has focused on the maximization of the covered demand and/or the minimization of resources usage, such as traveling time. However, the specific needs of the populations and, in a broad sense, the consideration of fairness in the access to health services, have not been thoroughly explored. Indeed, visiting *large* localities ensures



(a) Instance 1 of Type A

(b) Instance 1 of Type B

(c) Instance 1 of Type C

(d) Instance 1 of Type D

Fig. 1 Distribution of the *primary locality* (purple star), as well as *large* (yellow dots), *medium* (green dots), and *small* (red dots) localities in the first instance of each type

enough potential patients as to exhaust the MC daily capacity without moving to several smaller localities. Moreover, larger localities are, in general, easier to serve or to access. Consequently, traditional approaches that maximize the covered demand tend to allocate services to localities with higher demand.

Inspired by the objectives of the FAM, the proposed formulations integrate the marginalization of the localities as a metric to manage their access to services, the rational being that more marginalized localities should be prioritized. However, this approach raises some difficulties in a *full-day stop* context, where MCs can only visit one locality per day. Indeed, visiting a locality having a demand smaller than the MC daily capacity leads to inefficiencies (i.e., idle time of the MC staff). Surplus variables p_i' representing the unused capacity allocated to a locality i can be used to ensure that small, highly marginalized localities are sufficiently served while guarantying the efficiency of the solutions.

To shed some light on the trade-off between fulfilling the demand in the smallest and most vulnerable localities, and wasting MC's capacity that could be used in other localities, we propose a set of experiments where the surplus variables are bounded to specific values, representing the tolerance of managers to accept less efficient solutions. To this end, we solved again the 40 instances presented before but limiting the surplus variables to 5%, 10%, 15%, 20%, 25% and 30% of the total capacity. The instances were solved in parallel using commercial solver Gurobi on one of the Digital Alliance of Canada's servers. Each task was allocated one CPU and 6 GB of memory. A GAP

		Day-based formulation				Trip-based formulation			
Type	Ins	T_1	Gap_1	T_2	Gap_2	T_1	Gap_1	T_2	Gap_2
A	1	2	0.10%	43	0.07%	97	0.07%	22569	0.10%
	2	2	0.00%	16	0.08%	170	0.10%	36000	18.49%
	3	9	0.00%	334	0.10%	1922	0.10%	36000	29.13%
	4	1	0.00%	103	0.10%	1	0.00%	36000	15.80%
	5	1	0.00%	87	0.00%	1	0.00%	21092	0.10%
	6	3	0.09%	118	0.08%	1757	0.10%	36000	10.37%
	7	21	0.00%	35	0.07%	539	0.10%	36000	19.89%
	8	1	0.00%	11	0.05%	1	0.00%	808	0.10%
	9	3	0.00%	14	0.10%	4	0.00%	3953	0.10%
	10	2	0.08%	11	0.09%	2	0.00%	708	0.10%
B	11	1.8	0.00%	152.5	0.09%	10.6	0.02%	36000	16.18%
	12	5	0.07%	816	0.10%	14646	0.10%	36000	24.42%
	13	1	0.00%	16	0.10%	1	0.00%	28010	0.10%
	14	1	0.03%	1906	0.10%	1	0.00%	36000	52.26%
	15	2	0.00%	17	0.10%	1	0.00%	5758	0.10%
	16	1	0.00%	392	0.10%	2	0.00%	36000	25.44%
	17	2	0.09%	38	0.08%	82	0.10%	36000	15.15%
	18	1	0.00%	28	0.00%	2	0.00%	36000	13.02%
	19	3	0.00%	19	0.04%	1	0.00%	36000	19.52%
	20	1	0.00%	74	0.09%	4	0.00%	4787	0.10%
C	21	7	0.00%	1365	0.10%	10	0.00%	36000	29.66%
	22	22	0.02%	534	0.09%	6	0.02%	36000	41.92%
	23	9	0.00%	2593	0.10%	7	0.00%	36000	57.60%
	24	24	0.05%	3198	0.10%	18000	0.53%	36000	40.59%
	25	6	0.08%	22419	0.10%	2	0.00%	36000	49.40%
	26	22	0.00%	481	0.07%	4	0.00%	36000	46.97%
	27	12	0.04%	11858	0.10%	3	0.04%	36000	34.76%
	28	15	0.00%	12332	0.10%	1884	0.10%	36000	59.67%
	29	8	0.00%	18	0.04%	8	0.00%	36000	41.15%
	30	17	0.00%	19297	0.10%	29	0.00%	36000	58.06%
D	31	2	0.00%	63	0.10%	2	0.00%	35160	15.66%
	32	1	0.00%	18	0.10%	1	0.00%	25607	10.42%
	33	3	0.00%	11	0.06%	1	0.00%	26692	16.68%
	34	1	0.00%	13	0.04%	1	0.00%	27637	10.74%
	35	9	0.00%	136	0.10%	5	0.00%	36000	19.87%
	36	4	0.00%	267	0.07%	4	0.00%	36000	21.54%
	37	5	0.09%	208	0.09%	5	0.00%	36000	27.22%
	38	3	0.00%	67	0.10%	1	0.00%	24635	12.63%
	39	2	0.00%	220	0.10%	1	0.00%	20746	16.17%
	40	4	0.00%	180	0.08%	1	0.00%	24370	12.15%

Table 6 Solving times and optimality gaps produced by the *day-based* and *trip-based* formulations for the first and second stages of the lexicographic method

of 0.001 was set, and the solving time was limited to one hour per stage in the lexicographic method previously described and considering an ϵ of 0.02.

To analyze the results, other than the total covered demand and the total distance traveled by the MC, we looked at the sum of the covered weighted demand (i.e., the covered demand multiplied by the marginalization index of the localities), and the number of localities of each type that received service from the MC. Using this information, Figure 2 shows, for each of the considered values limiting the surplus, the percentage of total covered demand (line in red), the percentage of the sum of the covered weighted demand (line in purple), and finally, the percentage of each type of locality being served (blue, yellow and green bars).

Figures 2(a) to 2(d) show that, as hypothesized, there is an inverse relation between the total covered demand and the weighted oned which includes the population marginalization score. In other words, maximizing the covered demand does not seem to serve the most marginalized populations. Figures 2(a) to 2(d) also illustrate how relaxing the limitation on the surplus impacts the structure of the produced solutions. It can be observed that, independently of the geographical distribution and the total number of localities, accepting higher surplus (i.e., unused capacity) lead to serving more *small* localities, therefore increasing the covered weighted demand, but decreasing the total covered demand. However, managers must handle surplus wisely, because it quickly translates into inefficiencies and wasting of the MC's capacity. For instance, Figure 2(a) shows that the average total covered demand decreases from 74% to 55%, for the instances of type A when the limit on the surplus increases from 5% to 30%. This drop of almost 20% in the MC efficiency means that MC is not used during four days of each 20-days planning horizon. Managers must decide to which extent they are willing to allow MC's idle time, which is also an opportunity for the medical staff to perform administrative tasks unrelated to medical consultations.

In this vein, when looking at Figures 2(a) to 2(d), there seems to be an "equilibrium point" for each type of instance where the most vulnerable communities can be attended without compromising significantly the efficient use of resources. In fact, it can be observed that accepting up to 15% of surplus allows to cover (at least partially) demand from all the *small* localities which might be a reasonable managerial objective.

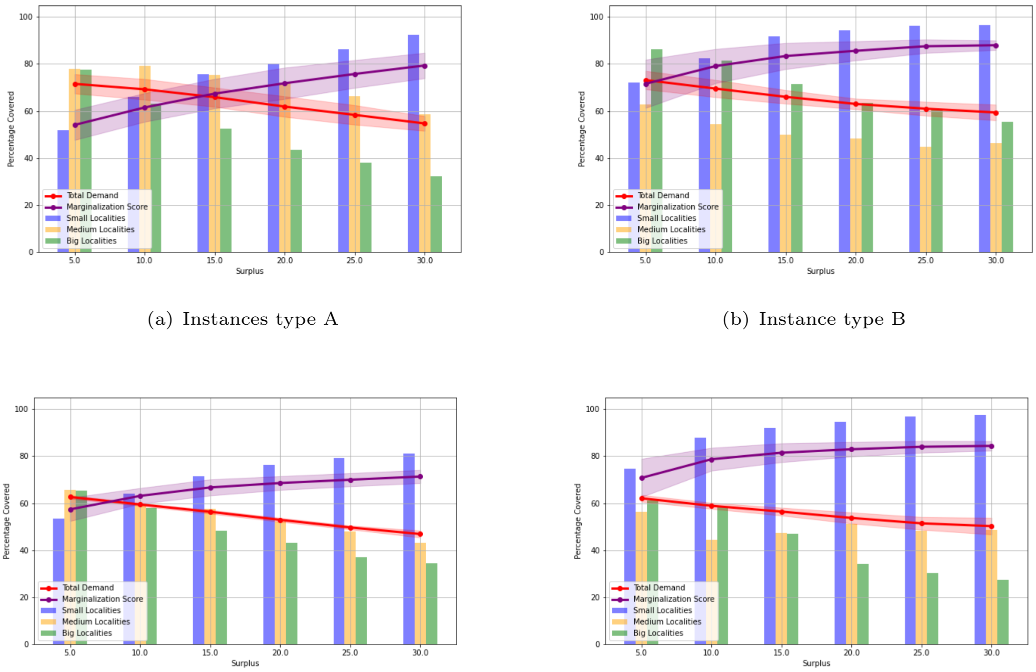
Finally, we also observed some differences in results depending on the geographical distribution of localities. Unsurprisingly, when localities are distributed following a centralized pattern, as in Figures 2(b) and 2(d), it seems easier to achieve better results from the perspective of the total covered weighted demand, most likely because a larger number of *small* localities (*satellites*) can be served from *secondary localities*. Thus, in a single visit, the MC can attend more localities incurring less idle time. Therefore, managers must carefully take into consideration the geographical distribution of the localities and their characteristics when elaborating the routes for MCs.

5 Conclusion

The potential of MCs for improving access to healthcare by delivering ambulatory services to marginalized and out-of-reach populations have been extensively discussed in the literature. However, there exists a limited number of decision-support tools to aid managers in effectively organizing and handling MCs. Inspired by the managerial challenges faced by the Mexican program *Fomento a la Atención Médica* (FAM), this paper proposes and compares two distinct formulations for planning MC operations. These formulations ot only determine the MC route but also propose, by the introduction of the marginalization index (MI) related to population vulnerability, a prioritization scheme for the equitable allocation of the MC's capacity among the populations to serve.

Through numerical experiments on synthetic instances inspired by FAM data from Aguascalientes, Mexico, this research investigates the trade-off between effectiveness (maximizing capacity for vulnerable populations) and efficiency (minimizing unused capacity). The findings reveal an inverse relationship between total covered demand and prioritizing highly vulnerable populations, underscoring the challenge of achieving both objectives simultaneously. Additionally, the results demonstrate that smaller and more vulnerable localities benefit more when the MI is incorporated into the objective function.

However, this research has limitations that should be considered. It assumes a single region served by a single MC, whereas in practice, larger areas with multiple MCs are required. Future research should focus on developing formulations for planning multiple MCs across larger territories. Moreover, the study assumes a fixed MC capacity based on average service time per patient, which may not reflect the heterogeneous care provided in practical contexts. Formulations that account for various types of patients and services are needed to better address patient heterogeneity.



(a) Instances type A (b) Instance type B

(c) Instance type C (d) Instance type D

Fig. 2 Average total covered demand and average total weighted demand (i.e., affected by the populations' MI) for *small*, *medium* and *large* localities for each type of instances for various limits on the surplus

Lastly, the necessity for an appointment system is highlighted to ensure that only the population that can be treated attends the MC, given that not all demand will be met at each locality and people from *satellite localities* must travel to *secondary localities* for service.

Declarations

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