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Mobile Clinics Deployment for Humanitarian Relief: A Multi-Period Location-Routing Problem

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Abstract. Mobile clinic deployments are commonly used to provide healthcare services as part of humanitarian relief efforts. In this study, humanitarian relief is quantified as the benefit of covering locations and servicing the population. We present a multiperiod location routing problem (MLRP) model for the tactical planning of mobile clinic deployment that captures the time dependency nature of mobile clinic deployments for humanitarian relief. To solve the MLRP, we propose a set packing formulation that relies on the generation of routes. The optimization of the proposed model yields the selection of depots and the routes that will be performed at each time period through the planning horizon, i.e., the tactical plan. Results are presented for real world data from a mobile clinic deployment in Iraq, including sensitivity analyses on the modeling of covering and continuity, and the effect of strategic decisions, e.g., number of mobile clinics. Managerial insights are also presented.

Keywords: Mobile health units, healthcare delivery, healthcare coverage and continuity, location routing, set-packing formulation.

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1 Introduction

This paper presents an analytical approach and managerial insights to support mobile clinics deployment for humanitarian relief. As part of the 2030 Sustainable Development Goals, members of the United Nations (UN) pledged to "Ensure healthy lives and promote well-being for all at all ages" (UN, 2015). Therefore, the World Health Organization (WHO), a specialized agency of the UN, and its partners resort to mobile clinics to administer healthcare services to populations that do not have access to healthcare (WHO, 2016). A mobile clinic is a vehicle which transports healthcare providers and equipment to provide ambulatory health services (McGowan et al., 2020). In rural areas and in areas affected by conflit or disaster (Blackwell and Bosse, 2007; Gibson et al., 2011; Fox-Rushby and Foord, 1996), mobile clinics are often the only way to conduct healthcare (Du Mortier and Coninx, 2007). In fact, they allow for quick response and flexibility due to their ability to move (Wray et al., 1999), and can be equipped to respond to multiple healthcare issues (Blackwell and Bosse, 2007). They can also be used to prevent hospitalizations (Guo et al., 2001). On the other hand, according to the International Federation of the Red Cross and Red Crescent Societies (IFRC), mobile clinics are expensive to operate and their deployment represents a logistical challenge (Du Mortier et al., 2006).

The temporary nature of mobile clinics has led to a scarceness of documentation related to operations and procedures (Lehoux et al., 2007), even though two guides were commissioned in an effort to support their deployment for humanitarian relief (see Du Mortier et al., 2006; Du Mortier and Coninx, 2007). Eight questions to guide decision makers throughout the strategical, tactical, and operational planning were identified. The strategical questions include: "what is happening?", "what is important?", "what can be done?", and "with what will it be done?". During the strategic phase, decision makers must determine the appropriate numbers of mobile clinics, healthcare practitioners, and medical equipment, as well as the available budget. They must also select which locations will receive healthcare services by the mobile clinics. At the tactical phase decision makers must answer: "what will be done?" and "how will it be done?". According to the strategical decisions, decision makers must schedule the mobile clinics, which includes the frequency of visits, the days, and the time of day to deploy the mobile clinics to each location. Additionally, depending on the healthcare condition of the patients, more than one visit may be required to provide the needed healthcare. Finally, the operational questions include the "implementation" and "what was done?" (*i.e.*, after action reports).

This paper focuses on the optimization of the tactical plan, given its day-by-day execution, while also using the tactical-planning model to study the impact of strategical decisions. We aim to bridge the gap in the scientific literature relative to the complexity of mobile clinics deployment for humanitarian relief. We therefore model the tactical planning of mobile clinics deployment as a multiperiod location routing problem (MLRP), an extension of the location routing problem (LRP) (Prodhon and Prins, 2014), that is well suited to capture the time dependency of mobile clinics deployment. Multiple-period representation of time provides the means to capture the fact that the time and frequency of visits can encourage or discourage patients from seeking healthcare (McGowan et al., 2020), as well as the impact of providing healthcare during a given moment in time (e.g., half day, day, week) on service in subsequent periods. In the MLRP, we consider a homogeneous fleet, as medical staff is assigned to teams of the same composition (Du Mortier and Coninx, 2007), and multiple origin and destination depots, as humanitarian crises can affect people over large areas.

Traditionally, MLRP formulations minimize the transportation costs as well as the costs of opening a depot over a planning horizon. However, in humanitarian operations, while costs are important, the primary goal is to maximize the relief provided to vulnerable populations (Leseure et al., 2010). In this paper, we quantify humanitarian relief as a benefit of covering locations and servicing the population, and propose a new MLRP formulation where the benefit is maximized. This benefit is twofold: 1) *coverage* (also known as physical accessibility), defined as "availability of good health services within reasonable reach of those who need them" (WHO, 2014); and 2) *continuity* of care, defined as "the degree to which a series of discrete health care events is experienced by people as coherent and interconnected over time and consistent with their health needs and preferences" (WHO, 2018). Continuity of care is important to consider as it reduces hospitalization in children (Christakis et al., 2001), improves quality of care for patients with chronic diseases (Gill et al., 2003), increases beneficiary satisfaction (Gray et al., 2018), decreases the risk of emergency visits (Bayliss et al., 2015), and increases survival in older populations (Maarsingh et al., 2016).

The contributions of this paper are as follows. First, we model coverage and continuity of care through a benefit function. Second, we model the MLRP with a set-packing formulation, which seeks to maximize the total benefits (Rasmussen and Larsen, 2011). Our formulation relies on the generation of routes, which is possible in this context as the number of stops a given mobile clinic can do is usually small. Solving our model yields the selection of depots and the routes that will be performed at each time period through the planning horizon. Third, this work is conducted as part of an ongoing collaboration with an international non-governmental organization that deploys mobile clinics for humanitarian relief. While our approach is sufficiently general to support any mobile clinic deployment, our model is tested on real world data. We conduct sensitivity analyses on the modeling of covering and continuity, as well as the effect of strategic decisions (e.g., number of mobile clinics), and derive managerial insights.

The remainder of this paper is organized as follows. In Section 2 a literature review is presented. Section 3 presents the problem definition and the proposed mathematical model. In Section 4, computational results and managerial insights are discussed. Finally, conclusions are derived in Section 5.

2 Literature review

Humanitarian relief operations can benefit from operations research and management science (OR/MS) techniques (Jahre et al., 2007). However, humanitarian operations have particularities, such as the requirement of rapid response, the presence of non-traditional networks, and the lack of information technology systems and documentation, that hinder the direct implementation of methods and approaches developed for non-humanitarian operations (Oloruntoba and Gray, 2006). In the literature, authors have underlined the need for studies that aid in the planning phases of humanitarian relief (Overstreet et al., 2011). Even though there has been a significant increase in the literature on humanitarian relief, the majority of the studies have been of qualitative nature and, therefore, there is a gap on quantitative methods (Jabbour et al., 2017). In this section, we position our contributions in the literature. First, we discuss previous studies that propose mathematical models to tackle mobile clinic deployments. Then, we examine how coverage and continuity have been addressed in the literature. Finally, we briefly present studies that formulate problems as location routing problems in non-humanitarian and humanitarian context, as well as studies that consider multiperiod location routing problems.

2.1 Mobile clinics

To the best of our knowledge, three studies have proposed OR/MS approaches for mobile clinics deployment. Hodgson et al. (1998) and Doerner et al. (2007) address mobile clinics deployment for humanitarian relief as a covering tour problem (CTP). In the CTP, mobile clinics are located in villages where a maximum number of patients can access it while respecting a maximal walking distance. Hodgson et al. (1998) aim to minimize the travel time required for a mobile clinic to cover all the demand and apply the branch-and-cut algorithm developed by Gendreau et al. (1997). Their formulation was tested on instances derived from a humanitarian deployment in Ghana. Doerner et al. (2007) added two additional criteria to the objective function, i.e., minimizing the distance and maximizing the population coverage. To solve the problem they develop two multicriteria metaheuristics and solve instances based on a mobile clinic deployment for humanitarian relief in Senegal.

More recently, Savaşer (2017) have proposed a periodic location routing problem (PLRP) formulation for mobile clinics deployment in rural areas. In the PLRP, the problem consists of selecting depots, assigning fixed periodic schedules for the mobile clinics, and selecting routes over a planning horizon, while minimizing the total travel distance. Routes starting and ending at a depot are planned daily but divided into two partial routes each corresponding to a time period (*i.e.*, half a day). Savaşer (2017) also consider a predetermined frequency of visits at each location, and a predetermined time between visits. The author develops a heuristic and test the model on instances derived from a deployment of mobile clinics in Turkey.

2.2 Coverage and continuity of care

In this paper, we use the OR/MS literature definition of coverage to represent the physical accessibility to healthcare provided by a mobile clinic. Therefore, a location is covered if the node is visited or within easy access from a visited node (Current and Schilling, 1989). Previous authors have used coverage modeling techniques to address, for example, the delivery of medical supplies in the Netherlands (Veenstra et al., 2018), the location of distribution centers for disaster relief (Burkart et al., 2017), the location of satellite distribution centers (Naji-Azimi et al., 2012), and mobile clinic operations (Hodgson et al., 1998; Doerner et al., 2007). This also makes sense in the context considering that travel time and physical barriers could negatively impact healthcare (Martin et al., 2002; Agyemang-Duah et al., 2019).

Continuity of care has been previously addressed in home healthcare routing and scheduling problems (Fikar and Hirsch, 2017). Three types of continuity of care have been highlighted, that is, management, informational, and relational (Maarsingh et al., 2016), and authors usually consider continuity of care as the ongoing care by the same healthcare practitioner. Commonly authors incorporate continuity of care by minimizing the number of healthcare practitioners assigned to a patient over the planning horizon (Nickel et al., 2012; Milburn and Spicer, 2013; Bowers et al., 2015). Carello and Lanzarone (2014) also suggest three types of patients (requiring hard, partial, or no continuity of care) and minimize the cost associated with reassignments of healthcare practitioners. Wirnitzer et al. (2016) propose different objectives, i.e., minimizing the number of different healthcare practitioners per patient tour, minimizing the different number of healthcare practitioners per patient, minimizing the number of healthcare practitioners per patient relative to their needed frequency of care, and minimizing the number of switches between assigned healthcare practitioners per patient over the planning horizon. Grenouilleau et al. (2019) maximize the score, which represents the strength of the beneficiary-healthcare practitioner, and thus continuity of care. Cinar et al. (2019) maximize the prize collected per patient per visit. Mosquera et al. (2019) argue that continuity of care may be impossible to satisfy and, hence, impose a soft constraint on the number of visits by a healthcare practitioner to a specific patient. Grenouilleau et al. (2020) also include the time and day as part of continuity of care.

2.3 Location routing problem

The LRP is within the field of location analysis, and integrates vehicle routing decisions with facility location (Nagy and Salhi, 2007), as considering both decisions separately leads to sub-optimal decisions Salhi and Rand (1989). For recent literature reviews on the LRP please refer to Prodhon and Prins (2014) and Drexl and Schneider (2015). Location routing implies that when selecting the locations, where goods or services will be delivered and provided, the routes connecting all the locations are also considered. The LRP decisions include the number, size, and location of the depots, the allocation of demand points to depots, and the routing of vehicles (Lopes et al., 2013). Moreover, depots and vehicles can be capacitated or uncapacitated. In general, the literature related to the LRP has focused on minimizing costs (*i.e.*, fixed cost, depot selection cost, and route selection) (Prodhon and Prins, 2014). To solve the LRP, many exact algorithms have been proposed such as branch-and-price (Berger et al., 2007) and branch-and-cut algorithms (Belenguer et al., 2011). Tighter solution bounds are derived by Contardo et al. (2013a) and Contardo et al. (2013b) while using exact separation procedures and column generation. Finally, Nagy and Salhi (2007) underscore that only one fifth of the LRP literature is application oriented and Prodhon and Prins (2014) call for further developments and more realistic problems.

2.3.1 Location routing for humanitarian relief

To aid in the tactical planning of humanitarian relief, many location science-based approaches have been proposed. Some of the applications include the location of disaster relief distribution centers (Balcik and Beamon, 2008), food distribution centers (Rancourt et al., 2015), temporary hubs for disasters (Stauffer et al., 2016), and collaborative distribution centers (Balcik et al., 2019). Similarly, many routing based approaches have been proposed for humanitarian relief. Some applications include the delivery of medical and non-medical supplies (Hamedi et al., 2012; Naji-Azimi et al., 2012; Balcik et al., 2008; Parvin et al., 2018), and the evacuations after a disaster or crisis (Victoria et al., 2015).

To the best of our knowledge, only a few studies combine location and routing decisions for humanitarian relief. Yi and Özdamar (2007) propose a LRP to support healthcare operations and evacuation after a humanitarian crisis. The allocation of medical personnel to medical centers and emergency units are taken as location decisions, whereas the commodities needed to provide healthcare are routed from distribution centers and wounded people are routed from affected areas. Balcik (2017) proposes to model the selection of sites for evaluations of post-disaster conditions as a variant of the LRP, known as the selective assessment routing problem. In this problem, a subset of sites must be selected to conduct a needs assessment and vehicles are used to visit these sites. Cherkesly et al. (2019) propose a location-routing approach for the network design of community health workers in underserved areas, where the recruitment of community health workers and supervisors are taken as location decisions, while the training of community health workers by supervisors are modeled as routing decisions. In addition, a maximum coverage radius is imposed on community health workers. More recently, Arslan et al. (2019)

propose a location routing approach for the placement of refugee camps and the delivery of public services to refugee camps in Turkey, where refugee camps must be located and the delivery of public services to the camps must be conducted.

2.3.2 Multiperiod location-routing

The MLRP considers the LRP (Prodhon and Prins, 2014) over multiple periods. Hence, at each period the selection of depots, locations, and routes can change, while not all decisions must be reevaluated at every time period. In addition, decisions taken on the previous periods will affect decisions on subsequent periods. Drexl and Schneider (2015) higlight the scarcity of the MLRP literature and, to the best of our knowledge, only three studies propose solution approaches to the MLRP. Albareda-Sambola et al. (2012) consider a MLRP with decoupled time scales, which allows for the location decisions to be modified at predetermined periods. The authors propose an arc-variable based MIP model and solve it by applying a relaxation to the routing decisions. Tunalıoğlu et al. (2016) introduce the MLRP arising from the collection of olive oil mill wastewater and propose a adaptive large neighbourhood search metaheuristic. Finally, Moreno et al. (2016) introduce a multi-product multimodal stochastic MLRP arising in emergency relief logistics. They propose a heuristic based on the decomposition of decision variables into discrete disjoint subsets by time periods, emergency scenarios, and stochastic stages, and solving each disjoint subproblem by relaxing all variables that are not in the subproblem.

3 Problem definition and mathematical formulation

In this section, we first explain the MLRP for the context of mobile clinics in remote regions and war zones. Then, we present the notation and formulate the problem with a set packing formulation.

3.1 The MLRP for mobile clinics deployment

In our context, a set of villages in need of healthcare is identified. At each time period (e.g., each day) of the finite planning horizon, each mobile clinic departs from and returns to a potential depot, while visiting a subset of villages. Potential depots include permanent healthcare facilities and warehouses that can securely hold medical equipment. They also have a fixed opening cost and remain unchanged throughout the planning horizon. Each route must respect the capacity of the mobile clinics which are twofold, that is a maximal number of patients visited (treated) per time period, and a maximal duration.

Given the capacity of the mobile clinics and the size of the fleet, not all villages can be serviced. Covering a village also requires time to coordinate for the visits, which is represented by a fixed coverage cost. In addition, covering each village is associated with a fixed coverage benefit, while the number of visits (treatments) each person receives in a covered village is associated with a variable continuity benefit. The continuity benefit can remain constant or can decrease in time. Because medical consultations can require follow-ups while allowing days between visits, a minimal number of days between visits to each village is imposed, also denoted as a number of resting periods. Finally, a maximal budget is available over our planning period to cover the fixed costs to open depots and to service villages, as well as the variable transportation costs.

Therefore, in the MLRP for mobile clinics deployment, a homogeneous fleet of mobile clinics is available at each time period of a finite planning horizon, and must depart from and return to a set of potential depots (selected on the first period) while visiting a subset of villages in need. The decisions must respect the budget contraints (i.e., costs to open depots, costs to service village, and transportation costs), the capacity constraints (i.e., maximal number of patients and duration per mobile clinic), and the resting periods between visits. The objective consists of maximizing the total benefits which include coverage and continuity benefits.

3.2 Notation and mathematical model

The MLRP for mobile clinics is defined on a graph $\mathcal{G} = (\mathcal{N}^e \cup \mathcal{N}^c, \mathcal{A})$, where $\mathcal{N}^e$ is the set of nodes representing the potential depots, $\mathcal{N}^c$ is the set of nodes representing the villages to service, and $\mathcal{A}$ is the arc set. Each village $i \in \mathcal{N}^c$ is associated with a population $p_i \geq 0$. The fixed cost of operating a depot $i \in \mathcal{N}^e$ or servicing a village $i \in \mathcal{N}^c$ is given by c_i. Let $\mathcal{V}$ be the set of visit frequencies, i.e., the number of times a patient may be visited. The benefit is composed of a fixed coverage benefit β_i, associated with servicing village $i \in \mathcal{N}^c$, and of a variable continuity benefit β_i^v associated with servicing a patient at village i exactly $v \in \mathcal{V}$ times. The arc set is defined as $\mathcal{A} = \{(i,j) : \{i,j \in \mathcal{N}^e \cup \mathcal{N}^c\}\}$ and each arc $(i,j) \in \mathcal{A}$ is associated with a distance d_{ij}.

A homogeneous fleet of m capacitated mobile clinics is available, where the capacity Q of a mobile clinic is defined as the number of patients it can service in a time period. Let $\mathcal{T}$ be the set of successive time periods making up the planning horizon. The total costs of the deployment may not exceed the budget B and there are η resting periods between visits to each village.

Let $\mathcal{R}$ be the set of feasible routes, with $\mathcal{R} = \cup_{t \in \mathcal{T}} \mathcal{R}^t$, where $\mathcal{R}^t$ is the set of feasible routes at time period $t \in \mathcal{T}$. Each route $r \in \mathcal{R}$ is defined by an ordered vector of vertices $(i_1, i_2, ..., i_{n-1}, i_n)$, $i_k \in \mathcal{N}^e \cup \mathcal{N}^c, k = 1, \ldots, n$. Two types of routes are considered and included in $\mathcal{R}$, regular and repositioning routes. The former start and end at the same depot, i.e., $i_1 = i_n \in \mathcal{N}^e$, and visit a subset of villages $\{i_2, \ldots, i_{n-1}\} \in \mathcal{N}^c$. The later represent the possibility for mobile clinics to change depots during the planning horizon. These routes contain only two nodes ($n = 2$), i.e., i_1 and $i_2 = i_n$, start and end at different depots, i.e., $i_1, i_2 \in \mathcal{N}^e$ and $i_1 \neq i_2$, and visit no villages.

Each route $r \in \mathcal{R}$ is thus defined by a binary vector $\mathbf{a}$, where $a_{ir} = 1$, if route $r \in \mathcal{R}$ visits node $i \in \mathcal{N}^e \cup \mathcal{N}^c$, and zero otherwise. Each route is characterized by a total activity time, which includes the travel time, the setup time at each village θ, and the patient service time in each village (with γ representing the time to service a patient), and which respects the maximum duration allowed δ. Routes are further characterized by the number of patients served at each location, G_{ir}, and a cost, c_r, representing the transportation costs.

The MLRP is formulated as a set-packing formulation that seeks to maximize the total benefits. To formulate the problem, we use binary variables x_i equal to one if village $i \in \mathcal{N}^c$ is selected, y_i equal to one if depot $i \in \mathcal{N}^e$ is selected, λ_r^t equal to one if route $r \in \mathcal{R}^t, \forall t \in \mathcal{T}$, is selected, and ω_i^v equal to one if all the population at location $i \in \mathcal{N}^c$ has been covered at least v times. The formulation also uses continuous variables π_i^v defined between zero and one that indicate the percentage of people covered at village $i \in \mathcal{N}^c$ at least v times. The MLRP can then be modeled as

$$\text{maximize} \quad \sum_{i \in \mathcal{N}^c} \beta_i x_i + \sum_{i \in \mathcal{N}^c} \sum_{v \in \mathcal{V}} \beta_i^v p_i \pi_i^v \tag{1}$$

$$\text{s.t.} \quad \sum_{i \in \mathcal{N}^e} c_i y_i + \sum_{i \in \mathcal{N}^c} c_i x_i + \sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{R}^t} c_r \lambda_r^t \leq B, \tag{2}$$

$$\sum_{r \in \mathcal{R}^t} \lambda_r^t \leq m, \ \forall t \in \mathcal{T}, \tag{3}$$

$$a_{ir} \lambda_r^t \leq y_i, \ \forall i \in \mathcal{N}^e, t \in \mathcal{T}, r \in \mathcal{R}^t, \tag{4}$$

$$\sum_{r \in \mathcal{R}^t} a_{ir} \lambda_r^t = \sum_{r \in \mathcal{R}^{t+1}} a_{ir} \lambda_r^{t+1}, \ \forall i \in \mathcal{N}^e, \forall t \in \mathcal{T}, \tag{5}$$

$$\pi_i^v \leq x_i, \ \forall i \in \mathcal{N}^c, v = 1, \tag{6}$$

$$\sum_{r \in \mathcal{R}^t} a_{ir} \lambda_r^t + \sum_{t'=t+1}^{t' \leq t+\eta} \sum_{r \in \mathcal{R}^{t'}} a_{ir} \lambda_r^{t+1} \leq 1, \ \forall i \in \mathcal{N}^c, t \in \mathcal{T}, t \leq |\mathcal{T}| - 1 \tag{7}$$

$$\frac{\sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{R}^t} G_{ir} \lambda_r^t}{p_i} \geq \sum_{v \in \mathcal{V}} \pi_i^v, \ \forall i \in \mathcal{N}^c, v \in \mathcal{V}, \tag{8}$$

$$\pi_i^v \geq \omega_i^v, \ \forall i \in \mathcal{N}^c, v \in \mathcal{V}, \tag{9}$$

$$\omega_i^v \geq \pi_i^{v+1}, \ \forall i \in \mathcal{N}^c, v \leq |\mathcal{V}| - 1, \tag{10}$$

$$x_i \in \{0, 1\}, \ \forall i \in \mathcal{N}^c, \tag{11}$$

$$\pi_i^v \geq 0, \ \forall i \in \mathcal{N}^c, v \in \mathcal{V}, \tag{12}$$

$$\pi_i^v \leq 1, \ \forall i \in \mathcal{N}^c, v \in \mathcal{V}, \tag{13}$$

$$y_i \in \{0, 1\},\ \forall i \in \mathcal{N}^e, \qquad (14)$$
$$\lambda_r^t \in \{0, 1\},\ \forall r \in \mathcal{R}^t, t \in \mathcal{T}, \qquad (15)$$
$$\omega_i^v \in \{0, 1\},\ \forall i \in \mathcal{N}^c, v \in \mathcal{V}. \qquad (16)$$

The objective function (1) maximizes the total benefit computed as the sum of the coverage and individual continuity benefits. Constraint (2) imposes the budget available for the deployment during the planning horizon. Constraints (3) ensure that at most the number of mobile clinics available are used for the deployment. Constraints (4) are linking constraints imposing that a route must start and end at open depots only. Constraints (5) represent flow conservation constraints at each depot, i.e., they ensure that the number of mobile clinics that depart from a depot equals the number of mobile clinics that returned to that depot on the previous period. Constraints (6) impose that each visited village must also be covered. Constraints (7) ensure that there are η resting periods between visits to each village. Constraints (8) link the route variables with the percentage of the population covered v times. Constraints (9) and (10) ensure that patients can be serviced v times only if all patients in that village are serviced $v - 1$ times. Constraints (11)–(16) define the variable domain.

4 Computational results

We present the results of the numerical experiments and sensitivity analyses conducted to evaluate the impact on coverage and continuity of care of the methodology we propose for the deployment of mobile clinics. For increase realism and relevance, the experiments were conducted on data inspired by a project undertaken by our partner in Iraq. The implementation details and the Iraq network are explained in Section 4.1. Section 4.2 describes the proposed performance indicators. Computational results and managerial insights are presented in Section 4.3, while sensitivity analyses are conducted in Section 4.4.

4.1 Implementation details and characteristics of the network

The mathematical model was implemented on AMPL Version 20200110 and solved with CPLEX 12.9.0.0. All tests were performed on a Linux computer equipped with an Intel Core i7-3770 (3.40GHz) and 8Gb of RAM.

4.1.1 Characteristics of the network

Our problem was inspired by an ongoing collaboration with Première Urgence Internationale, an international NGO that deploys mobile clinics around the world. The data for testing the proposed model and analyzing the base case was derived from a deployment in Iraq consisting of 50 villages and 12 potential depots, shown in Figure 1. Bing Maps Distance Matrix API was used to compute the real-life distance in kilometers. Statistics, minimal (Min), maximal (Max), average (Average) and standard deviation (St. dev.), on road distances between villages as well as between depots and villages are presented in Table 1.

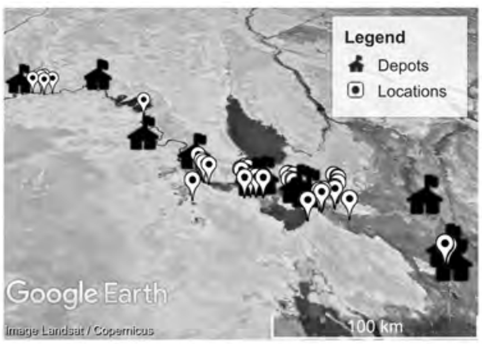

Figure 1: Location of potential depots and the villages to service

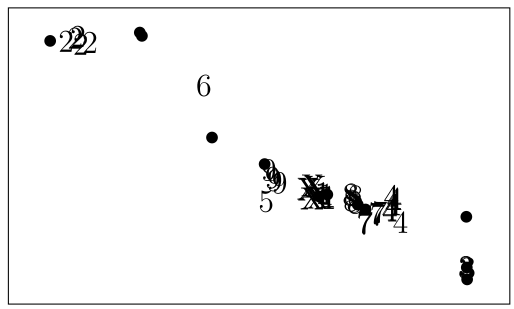

Figure 2: Location of potential depots (•) and ten clusters of villages to service (one symbol per cluster)

Table 1: Distance between villages and depots in km

Distance between	Min	Max	Average	St. dev.
Villages ($d_{ij}, \forall i, j \in \mathcal{N}^c$)	0.0	402.5	98.9	90.9
Depots and villages ($d_{ij}, \forall i \in \mathcal{N}^e, j \in \mathcal{N}^c$)	0.9	413.5	138.0	101.1

A team composed of medical and logistics personnel conducts a needs assessment in each village. This assessment reports the estimated population, the presence of chronic diseases, the presence of vulnerable groups (e.g., pregnant women, children, elderly), the access to vital resources (e.g., food and water), and the presence of humanitarian relief or access to aid. Using an assessment tool developed by our partner, this information is converted to a health score, denoted by $s_i, \forall i \in \mathcal{N}^c$. Table 2 presents the characteristics of the villages. We report minimal, maximal, average and standard deviation values for the population, as well as the score computed by our partner. These characteristics show that the villages are heterogeneous in terms of size (i.e., population), but that their healthcare needs are relatively similar. In fact, the data does not show a trend linking the size and the score of the villages.

Table 2: Characteristics of the villages

Cluster	Min	Max	Average	St. dev.
p_i	70	28,000	1,640.2	4,080.1
s_i	174	370	294.7	32.7

We considered the geography and the sparsity of the network, and identified ten clusters of villages (see Figure 2) by implementing a k-means algorithm using as input the latitude and longitude coordinates of the villages (see Appendix A for additional implementation details). When solving the MLRP, not all villages are covered. On the other hand, it is reasonable to assume that people from the non-covered villages could have access to healthcare in a nearby covered village (i.e., within reasonable walking distance). Therefore, clusters are used as a basis for geographical coverage. Table 3 presents for each cluster the number of villages, the minimal (Min.), maximal (Max.) and average (Average) distances, as well as the standard deviation (St. dev.), between the pairs of villages in each cluster.

Table 3: Characteristics of the clusters

Cluster	$\lvert\mathcal{N}^c\rvert$	Distance in km			
		Min	Max	Average	St. dev.
1	7	0.7	9.1	5.8	2.4
2	5	5.6	23.3	11.8	6.7
3	4	0.0	7.8	3.4	2.4
4	9	0.1	35.8	12.8	9.7
5	1	0.0	0.0	0.0	0.0
6	1	0.0	0.0	0.0	0.0
7	6	0.5	23.3	14.3	9.7
8	6	1.7	19.3	8.8	4.9
9	4	2.9	13.5	7.2	3.6
10 (X)	7	0.2	27.6	13.2	8.0

4.1.2 *Base* case

The *base* case is defined by setting the parameter values to those used by our partner. In terms of operations, a two-week (ten days, $|\mathcal{T}| = 10$) schedule is repeated over a two-month period. The fleet is composed of five mobile clinics ($m = 5$). A mobile clinic with a single doctor must provide services each work day to 50 beneficiaries ($Q = 50$). This capacity is imposed by our partner as well as by the Ministry of Health. Our partner also imposes a two-day resting period ($\eta = 2$) between visits to a given village. A maximum budget of \$5,000 for each two-week planning period ($B = 5000$) is available to cover transportation costs, the costs of servicing a village, and the costs of using a depot. Moreover, if a mobile clinic visits more than one village, its capacity Q is divided equally according to the number of stops, denoted as *equal proportion*. For example, given $Q = 50$ and a route covering two villages, 25 people will be serviced in each village. Historical data shows that the minimum service time for a single beneficiary is five minutes ($\gamma = 5$). Given that each work day lasts six hours and that 50 people must be serviced, this leaves 110 minutes for setting up the mobile clinic at each village and traveling between villages and depots. Considering that the estimated set up time at each location is 30 minutes ($\theta = 30$), at most three villages can be visited by a single mobile clinic. A total of 2,711 feasible routes were generated for each time period.

The coverage benefit for the *base* case is measured by testing fixed values of β_i from 0 to 700, in increments of 50. Note that after discussions with our partner, their current coverage benefit is $\beta_i = 0$. The continuity benefit is computed as $\beta_i^v = (\alpha_v - \alpha_{v-1})(s_i/p_i)$, where the individual score obtained through the needs assessment is multiplied by a percentage $(\alpha_v - \alpha_{v-1})$ for the incremental value of servicing a beneficiary v times. Our partner uses *linear marginal benefits* computed as

$$\alpha_v = v\frac{1}{|\mathcal{V}|},$$

which implies that each visit is of equal importance.

4.2 Performance indicators

We propose a number of relevant performance indicators to analyze the results obtained with our solution approach for mobile clinics deployment in remote regions and war zones. These performance indicators are grouped in two categories, coverage and continuity, and defined in Table 4. We measure coverage of care through geographical coverage, community coverage, and population coverage. To measure geographical coverage, we compute the number of covered clusters. To measure community coverage, we compute the number of covered villages. To measure population coverage, we compute the percentage of people visited at least once in covered villages. A continuity of care indicator, on the other hand, should allow to measure if people are visited more than once to better monitor patients' health. Continuity of care is thus measured with the percentage of people visited at least v times in covered villages, with $v \geq 2$.

4.3 Results for the *base* case

We present in this section the detailed results obtained for the *base* case data set and derive managerial insights. Detailed computational results are reported in Appendix B.

Table 4: Performance indicators

Name	Description
Coverage performance indicators	
COV-C	Number of covered clusters
COV-V	Number of covered villages
COV-1	Percentage of people visited at least once in covered villages
Continuity performance indicators	
CNT-v	Percentage of people visited at least v times in covered villages

All solutions are found between 14 to 390 seconds, with an average computational time of 163 seconds. When increasing β_i, a higher importance is given to coverage (rather than continuity). Our analysis allows to find solutions which offer a good compromise between coverage and continuity of care.

First, we analyzed the number of covered clusters. Out of the ten clusters, eight clusters are covered with $\beta_i = 0$ and nine with $\beta_i \geq 50$. One cluster containing exactly one village remains non-covered in all the solutions and this makes sense in practice as the cluster is the furthest away from all other clusters. Note that more than 25% and more than 38% of the non-covered villages are within 5km and 7.5km of their nearest covered village, and the maximal distance is 20.7km. This suggests that people living in non-covered villages could walk (or use another mode of transport) within a reasonable time to their nearest covered village to receive healthcare if needed.

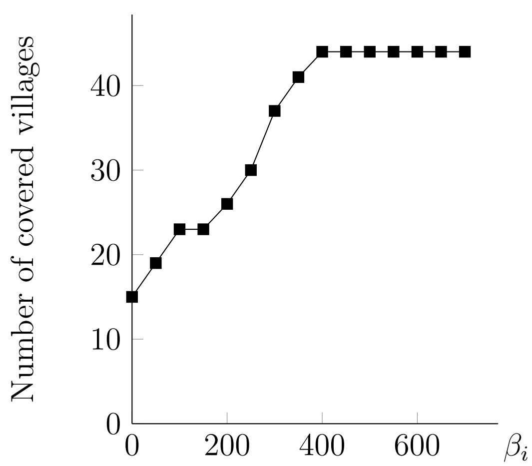

Figure 3: Number of covered villages (*base* case)

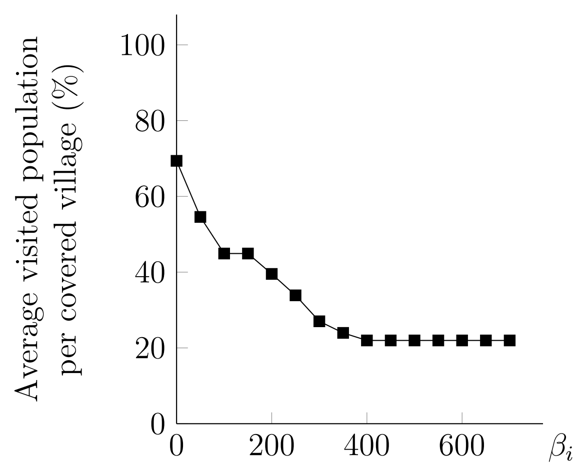

Figure 4: Average proportion of the population visited at least **once** (*base* case)

Second, we analyzed the number of covered villages as well as the average proportion of the population visited at least once, see Figures 3 and 4, respectively. Out of the

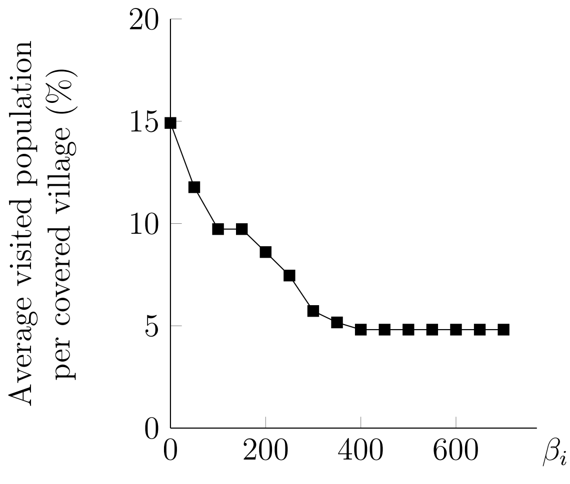

Figure 5: Average proportion of the population visited at least **twice** (*base* case)

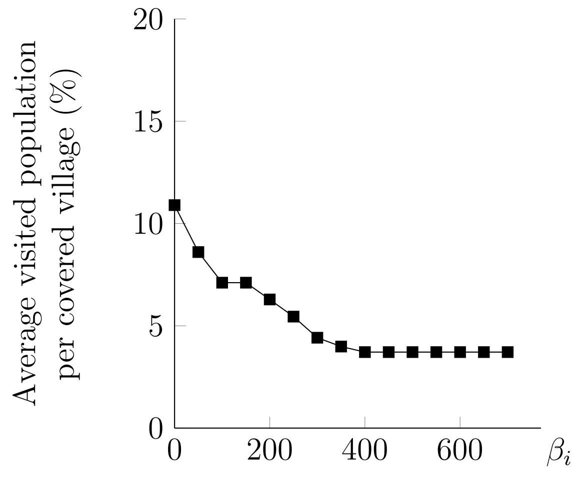

Figure 6: Average proportion of the population visited at least **thrice** (*base* case)

50 villages, 15 to 44 villages can be covered and more villages are covered as the value of β_i increases. In addition, the average proportion of people visited at least once in the set of covered villages ranges from 22% to 69%, and decreases when β_i increases. More precisely, when $\beta_i = 0$, only 15 villages are covered and an average of 69% of the population in these villages is visited at least once, while the maximum number of covered villages is reached when $\beta_i \geq 400$ with 22% of the population covered at least once on average. Therefore, increasing the value of β_i allows to cover more villages while the proportion of people visited at least once decreases.

Third, we analyzed the average proportion of the population visited twice and thrice, see Figures 5 and 6, respectively. In the set of covered villages, the average proportion of people visited at least twice and thrice ranges from 5% to 15%, and from 4% to 11%, respectively. In addition, most people visited twice are also visited thrice. Therefore, a reasonable value for continuity of care seems to be reached when $200 \leq \beta_i \leq 300$. For these values, the average population visited at least twice and thrice varies from 6% to 9%, and from 5% to 6%, respectively.

Our results show that a reasonable compromise between continuity and coverage seems to be reached when $200 \leq \beta_i \leq 300$. For these values, the number of covered villages ranges from 26 to 37, while the average population visited at least once, twice, and thrice varies from 27% to 40%, from 6% to 9%, and from 5% to 6%, respectively.

4.4 Sensitivity analyses

In this section, we first analyze how adding and removing mobile clinics impact coverage and continuity of care. Given that the number of mobile clinics depends on donors, this analysis allows for a discussion with our partner and its donors to better understand how the program could benefit from additional mobile clinics. Second, we analyze how the marginal benefit function and the number of visited individuals per route impacts the solutions. The goal is to validate the initial parameters set by our partner and the robustness of the solutions relative to changes in these parameters. For these two analyses, we compute the impact on the number of covered villages and the average proportion of the population visited at least once, twice, and thrice. The impact on the number of covered villages is computed as (COV-V$_\alpha$ − COV-V)/COV-V, where COV-V$_\alpha$ is the number of covered villages for a given setting and COV-V is the number of covered villages for the *base case*. The impact on the percentage of people visited at least once and more than once are computed as (COV-1$_\alpha$ − COV-1)/COV-1, (CNT-v_α − CNT-v)/CNT-v, respectively, where COV-1$_\alpha$ and CNT-v_α are the average proportions of population visited at least once and at least v times ($v \geq 2$) for a given setting, and where COV-1 and CNT-v are the average proportions of population visited at least once and at least v times ($v \geq 2$) for the *base* case. Detailed computational results are reported in Appendix B.

4.4.1 Impact of the number of mobile clinics

The impact of the number of mobile clinics on system performance was analyzed by removing the budget constraint ($B = \infty$) and increasing the number of mobile clinics from $m = 1$ to $m = 30$. Because the current number of mobile clinics (i.e., $m = 5$) used by our partner depends on funding, this analysis aims to show how an increase in funding could improve coverage and continuity of care. For conciseness reasons, we only report the results with $\beta_i = \{0, 100, 200, 300, 400\}$, as similar results were obtained with the other tested values of β_i. All solutions are found within 1,500 seconds, with an average of 35 seconds.

First, we analyzed the impact on the number of covered clusters. Independently on the value of β_i, when increasing the number of mobile clinics, more clusters are covered. For our network, the maximal number of covered clusters is reached when $m \geq 5$. In addition, at most 50% of the clusters are covered when $m \leq 3$. Therefore, while adding mobile clinics (i.e., $m \geq 6$) does not increase the number of covered clusters, removing some (i.e., $m \leq 4$) will significantly decrease the number of covered clusters and the geographical coverage of the program.

Second, we analyzed the impact on the number of covered villages as well as the

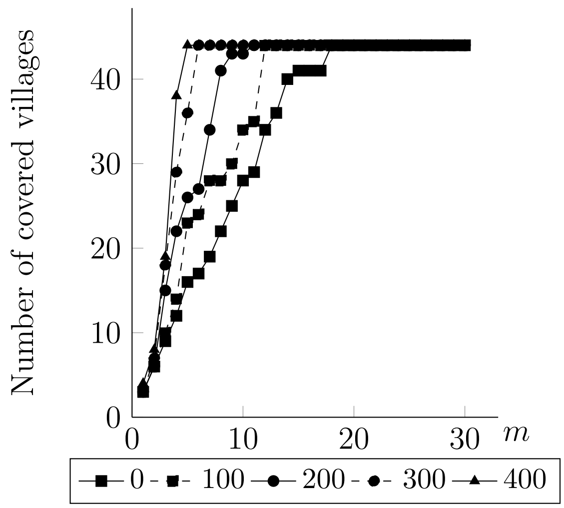

Figure 7: Number of covered villages ($B = \infty$)

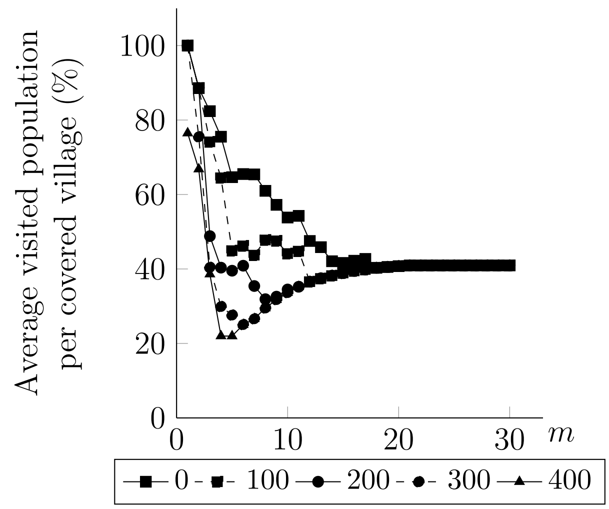

Figure 8: Average proportion of the population visited at least **once** ($B = \infty$)

average proportion of the population visited at least once, see Figures 7 and 8, respectively. Our results show that the number of covered villages increases as the number of mobile clinics increases, and this increase is larger for higher values of β_i. With all values of β_i, the maximal number of covered villages is reached with 18 mobile clinics, while at least 40 villages are covered with 14 mobile clinics. Given the current number of mobile clinics (i.e., $m = 5$), an increase of one mobile clinic usually allows to cover one or two additional villages, while an increase of two mobile clinics has a higher marginal impact on the number of covered villages. Removing mobile clinics on the other hand decreases the community coverage of the program, and at most ten villages are covered when $m \leq 3$. As the number of covered villages increases, the average proportion of the population visited at least once decreases, but it stabilizes at around 40% with at least 14 mobile clinics. This decrease does not imply that the number of people visited once decreases. On the contrary, when the number of mobile clinics increase, the total visited population increases. Given possible additional funding, increasing the number of clinics to 6 or 7 (one or two additional clinics) would allow for a significant better coverage.

Third, we analyzed the impact on the average proportion of the population visited twice and thrice, see Figures 9 and 10, respectively. Our results show that with a lower number of mobile clinics, the population covered twice and thrice is the highest which can be explained by the fact that very few villages are covered. On the other hand, when $m \geq 10$, it stabilizes.

Considering this analysis, when increasing the number of mobile clinics the geographical and community coverage increase, while the population coverage tends to decrease even though the number of visited people increases. We believe that given the limited

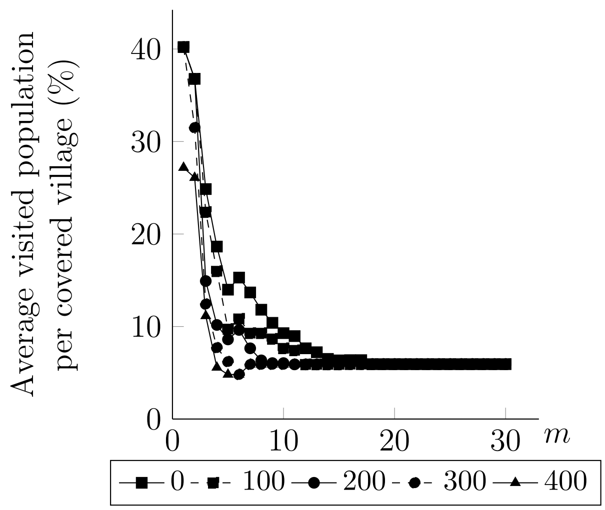

Figure 9: Average proportion of the population visited at least **twice** ($B = \infty$)

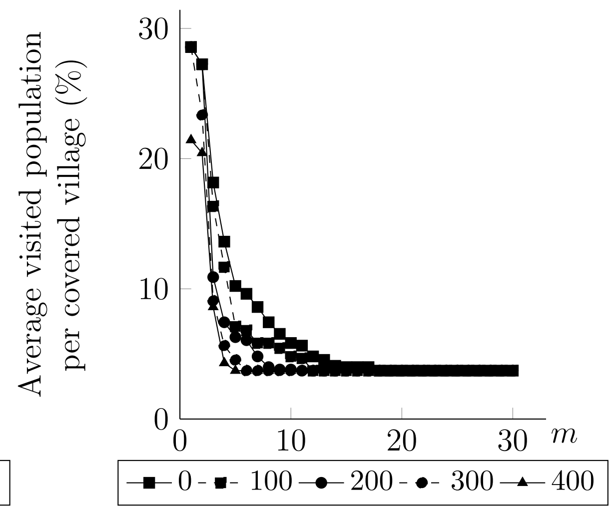

Figure 10: Average proportion of the population visited at least **thrice** ($B = \infty$)

funding, an addition of one or two mobile clinics should allow a better community and people coverage, while also allowing a reasonable continuity of care. We also believe that decreasing the funding would worsen dramatically the potential impact of the program.

4.4.2 Impact of the marginal benefit function

As indicated in Section 4.1.2, our partner models the continuity benefit with a linear marginal benefit function. Such a function implies, however, that all visits are of equal importance, while, in practice, the first visit is often the most critical. We thus aim to explore the impact on the system behavior and performance of different benefit functions, which represent the larger benefit of the first visit relative to subsequent ones. For this analysis, the value of $\beta_i^v, \forall i \in \mathcal{N}^c, v \in \mathcal{V}$, varies according to the function selected.

Two alternative benefit functions are proposed: *highly diminishing* and *smoothly diminishing* marginal benefits. These functions are inspired from modern economic theory of subjective value, also know as utility or marginal utility. Given the presence of continuity, an individual's rational preference can be represented mathematically by an utility function (Baumol, 1972; Mas-Colell et al., 1995), a diminishing marginal utility being usually assumed (Dittmer, 2005). For example, a child in need of vaccination could have a diminishing continuity benefit as the visit when the shot is administered is of greater importance than subsequent visits. With *highly diminishing* marginal benefits, the continuity benefit is computed as

$$\alpha_v = \begin{cases} a_h & \text{if } v = 1 \\ 0.5 - 0.5\alpha_{v-1} + \alpha_{v-1} & 1 < v < |\mathcal{V}| \\ 1 & v = |\mathcal{V}|. \end{cases}$$

With *smoothly diminishing* marginal benefits, the continuity benefit is computed as

$$\alpha_v = \begin{cases} a_s & \text{if } v = 1 \\ \min\{1, 0.5\sqrt{v} + c\} & 1 < v < |\mathcal{V}| \\ 1 & v = |\mathcal{V}|. \end{cases}$$

The values of a_h and a_s are set to impose a higher importance for the first visit, and c is set to determine the rate at which the benefit diminishes. With highly diminishing marginal benefits, the first visit has a weight of $a_h = 0.8$, and, therefore, the remainder, i.e., 0.2, is distributed in the subsequent visits. With smoothly diminishing marginal benefits, the first visit has a weight of $a_s = 0.5$, which is lower than with highly diminishing marginal benefits, i.e., $a_s \leq a_h$, thus allowing for a higher weight for the second visit. For our computational study, we set $c = 0.1$. Given $a_h = 0.8$, $a_s = 0.5$, and $c = 0.1$, Figures 11 and 12 present the behavior of the three marginal benefit functions according to two values for the maximal number of visits, i.e., $|\mathcal{V}| = \{3, 5\}$.

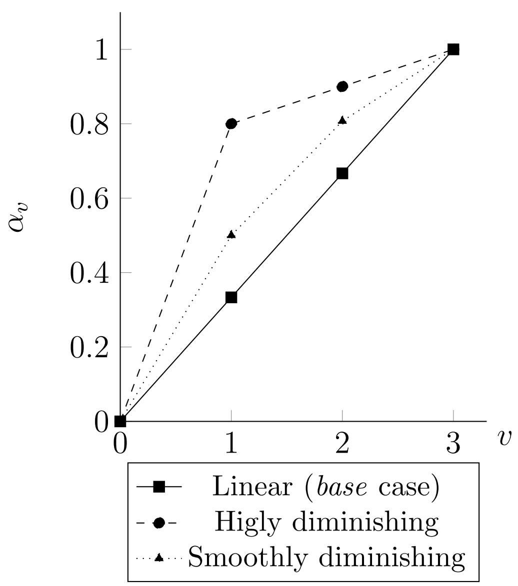

Figure 11: Marginal benefit functions, $|\mathcal{V}| = 3$

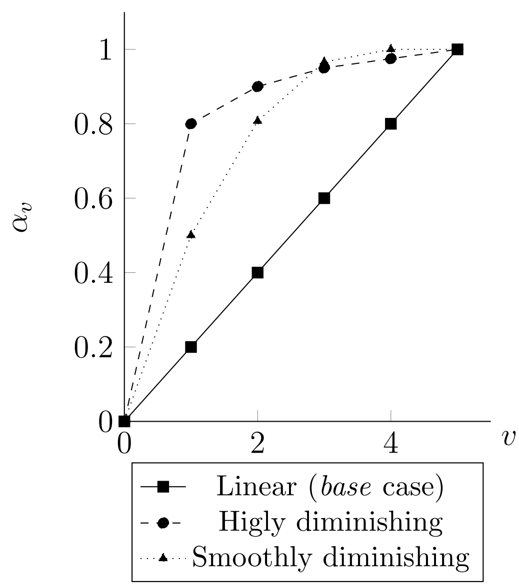

Figure 12: Marginal benefit functions, $|\mathcal{V}| = 5$

First, we analyzed the impact on the number of covered clusters. Out of the ten clusters, nine clusters are covered with highly and smoothly diminishing marginal benefits, independently of the value of β_i. Compared to linear marginal benefits, one additional

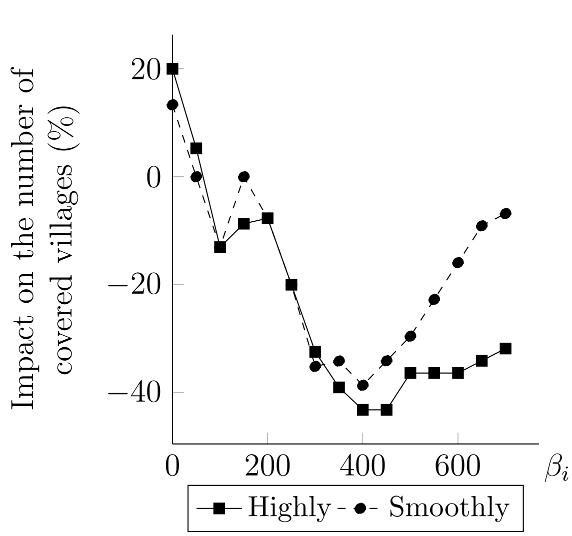

Figure 13: Impact on the number of covered villages when considering highly and smoothly diminishing marginal benefits ($m = 5$, $B = 5000$)

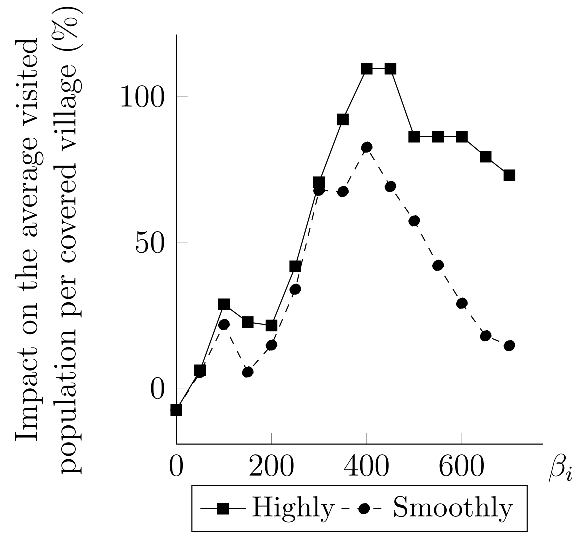

Figure 14: Average proportion of the population visited at least **once** with highly and smoothly diminishing marginal benefits ($m = 5$, $B = 5000$)

cluster is covered when $\beta_i = 0$, but the same clusters are covered when $\beta_i \geq 50$. Therefore, modifying the marginal benefit function does not seem to impact the number of covered clusters and allows for similar geographical coverage.

Second, we analyzed the impact on the number of covered villages and the average proportion of the population visited at least once, see Figures 13 and 14, respectively. Out of the 50 villages, the number of covered villages ranges from 18 to 30 and from 17 to 41, with highly diminishing and with smoothly diminishing marginal benefits, respectively. More villages are covered when $\beta_i \leq 50$, i.e., with highly diminishing marginal benefits three additional villages are covered when $\beta_i = 0$ and one additional village when $\beta_i = 50$, while with smoothly diminishing marginal benefits, two additional villages are covered when $\beta_i = 0$. When $\beta_i \geq 100$, linear marginal benefits provide a better coverage of the villages. In addition, for both highly and smoothly diminishing marginal benefits, there is an increase in the population covered at least once, which can be explained by the lower number of covered villages. Therefore, while the impact seems limited, a higher community coverage is obtained with linear marginal benefits, and a higher population coverage is obtained with highly diminishing marginal benefits.

Third, we analyzed the impact on the average proportion of the population visited twice and thrice, see Figures 15 and 16, respectively. With smoothly diminishing marginal benefits, our results show an increase in the average proportion of population covered at least twice when $\beta_i \geq 100$. The impact is at its highest when $\beta_i = 400$ considering the lower number of covered villages (27 and 44 covered villages with smoothly dimin-

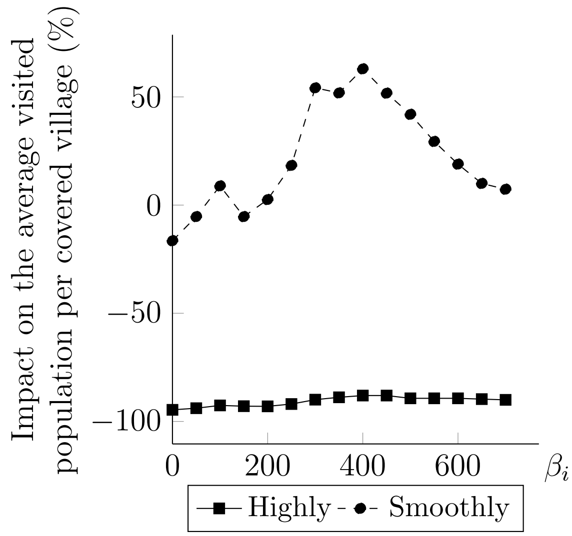

Figure 15: Average proportion of the population visited at least **twice** with highly and smoothly diminishing marginal benefits ($m = 5$, $B = 5000$)

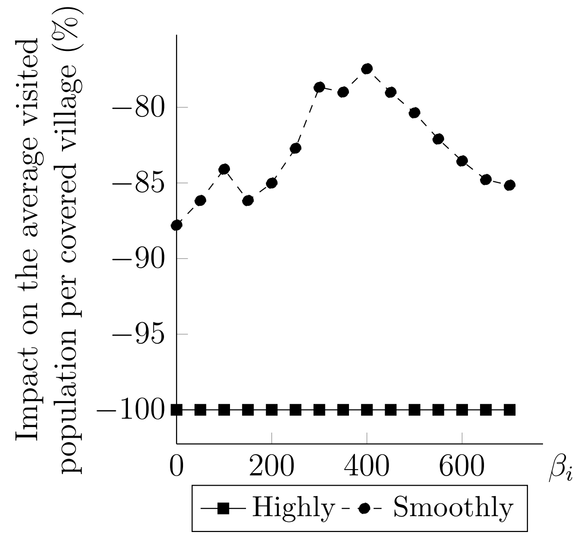

Figure 16: Average proportion of the population visited at least **thrice** with highly and smoothly diminishing marginal benefits ($m = 5$, $B = 5000$)

ishing marginal benefits and with linear marginal benefits, respectively). With smoothly diminishing marginal benefits, there is a decrease of at least 75% for the percentage of the population covered thrice, while with highly diminishing marginal benefits, no one is covered thrice and there is a decrease of a least 95% for the percentage of the population covered twice. Therefore, compared to highly diminishing and smoothly diminishing marginal benefits, linear marginal benefits offer a better continuity of care.

Our results indicate that when setting a higher value for the first visit, compared to the subsequent visits, a higher community coverage is reached with low values of β_i, i.e., with $\beta_i \leq 50$. On the other hand, with higher values of β_i, a higher population coverage is reached, while community coverage is decreased. In addition, linear marginal benefits seem to provide a better continuity of care. Therefore, the initial assumption of our partner of using linear marginal benefits allows a better continuity of care as well as a better community coverage. In addition, it is easier to compute as it requires less parametrization. Finally, our solution approach is not time sensitive with highly diminishing marginal benefits, i.e., all solutions are found within 187 seconds, with an average of 88 seconds. With smoothly diminishing marginal benefits, it is more sensitive as the maximal computational time is 4,769 seconds (one instance only is solved in more than 2,000 seconds), with an average of 747 seconds. We can thus conclude that using linear marginal benefits, which is easier to model, allows for robust solutions in a reasonable time.

4.4.3 Impact of the number of individuals visited per route

In its current program, our partner divides the number of visits equally in each route (see Section 4.1.2), which implies that all villages are of equal importance. In practice, villages are heterogeneous according to their population, their need of healthcare, their vulnerability score, and their accessibility to healthcare. In this section, we aim to examine if alternative ways of dividing the number of visits impact the solution.

Four alternative ways to determine the number of individuals visited per route have been considered, i.e., dividing the capacity: 1) proportional to the population of the villages, denoted as *population proportion* (*Pop.*); 2) proportional to the health score of the villages, denoted as *score proportion* (*Score*); 3) proportional to the vulnerability score (e.g., pregnant women, children, and elderly) of the villages, denoted as *vulnerability proportion* (*Vul.*); and 4) proportional to the accessibility to healthcare score of the villages, denoted as *accessibility proportion* (*Acc.*). For example, given the capacity Q, a route r_1 which covers exactly two villages $i_1, j_1 \in \mathcal{N}^c$, the number of people visited per village will vary according to the way we compute the number of people visited. With *population proportion*, the number of people visited will be

$$G_{i_1,r_1} = \left\lfloor Q\frac{p_{i_1}}{p_{i_1}+p_{j_1}} \right\rfloor \text{ and } G_{j_1,r_1} = \left\lfloor Q\frac{p_{j_1}}{p_{i_1}+p_{j_1}} \right\rfloor.$$

With *score proportion*, the number of people visited will be

$$G_{i_1,r_1} = \left\lfloor Q\frac{s_{i_1}}{s_{i_1}+s_{j_1}} \right\rfloor \text{ and } G_{j_1,r_1} = \left\lfloor Q\frac{s_{j_1}}{s_{i_1}+s_{j_1}} \right\rfloor.$$

With *vulnerability proportion*, the number of people visited will be

$$G_{i_1,r_1} = \left\lfloor Q\frac{s^1_{i_1}}{s^1_{i_1}+s^1_{j_1}} \right\rfloor \text{ and } G_{j_1,r_1} = \left\lfloor Q\frac{s^1_{j_1}}{s^1_{i_1}+s^1_{j_1}} \right\rfloor,$$

where $s^1_i, \forall i \in \mathcal{V}_c$ is the vulnerability score of village i computed by our partner. With *accessibility proportion*, the number of people visited will be

$$G_{i_1,r_1} = \left\lfloor Q\frac{s^2_{i_1}}{s^2_{i_1}+s^2_{j_1}} \right\rfloor \text{ and } G_{j_1,r_1} = \left\lfloor Q\frac{s^2_{j_1}}{s^2_{i_1}+s^2_{j_1}} \right\rfloor,$$

where $s^2_i, \forall i \in \mathcal{N}^c$ is the accessibility score of village i computed by our partner.

First, we analyzed the impact on the number of covered clusters. When $\beta_i \geq 50$, nine clusters are covered, while seven to nine clusters are covered when $\beta_i = 0$. Compared to *equal proportion*, when $\beta_i \geq 50$, the same clusters are covered which shows that geographical coverage remains constant independently on how the number of visits are computed.

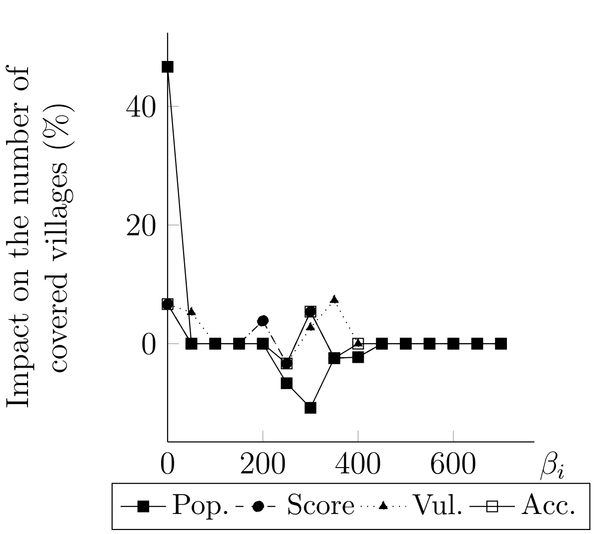

Figure 17: Impact on the number of covered villages when considering the number of visits in a route ($m = 5$, $B = 5000$)

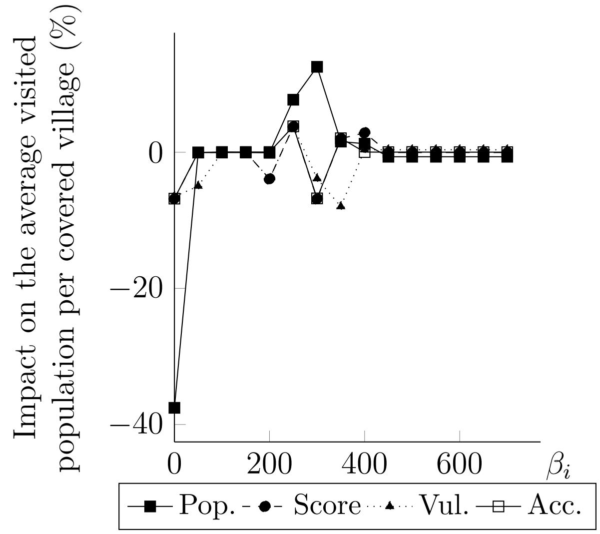

Figure 18: Average proportion of the population visited at least **once** when considering the number of visits in a route ($m = 5$, $B = 5000$)

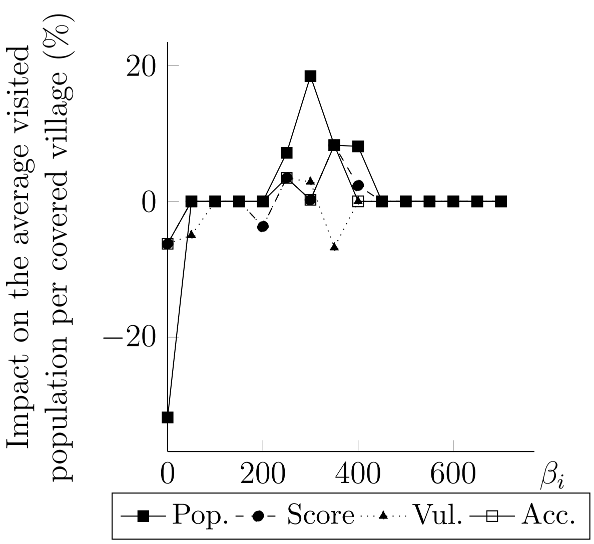

Figure 19: Average proportion of the population visited at least **twice** when considering the number of visits in a route ($m = 5$, $B = 5000$)

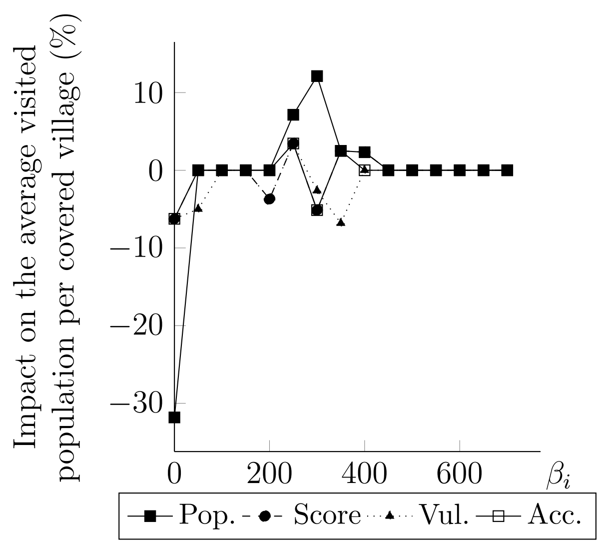

Figure 20: Average proportion of the population visited at least **thrice** when considering the number of visits in a route ($m = 5$, $B = 5000$)

Second, we analyzed the impact on the number of covered villages as well as the average proportion of the population visited at least once, see Figures 17 and 18, respectively. When $\beta_i = 0$, 15 to 22 villages are covered according to how the number of visits are determined. This increase in the number of covered villages can be explained by the fact that more than one optimal solution exists. When $\beta_i \leq 50$, the number of covered villages remains relatively similar independently on the number of visited individuals per route. In addition, the population covered at least once remains relatively constant, with the only exception of when $\beta_i = 0$, which is explained by the higher number of visited villages. Therefore, how the number of individuals are computed does not seem to have an impact on community and population coverage.

Third, we analyzed the impact on the average proportion of the population visited twice and thrice, see Figures 19 and 20, respectively. Our results show that the population covered at least twice and thrice remains relatively constant. On the other hand, when $\beta_i = 0$ the average population covered more than once decreases due to the increase in the number of covered villages. We can also notice a slight increase in the population covered more than once when $250 \leq \beta_i \leq 400$ due to the decrease in the number of covered villages.

Considering this analysis, we can see that when modifying how the number of visits are computed, the performance indicators as well as the solutions remain similar. In addition, the total computational time is not affected; all solutions are found within 260 seconds with an average of 100 seconds. Therefore, the initial rule to equally divide the number of visits, which is the simplest in practice, is the most efficient.

5 Conclusions

In this paper, we have introduced a set packing formulation for the MLRP for the deployment of mobile clinics for humanitarian relief. Our model seeks to maximize the total benefit, divided between coverage and continuity benefits. We have also proposed appropriate coverage performance indicators (number of covered clusters, number of covered villages, and percentage of people visited at least once in covered villages) and continuity performance indicators (percentage of people visited at least v times in covered villages).

Our solution approach was tested with real data from our partner, for a mobile clinic deployment in Iraq, and our results have allowed us to derive managerial insights in that context. Using our collaborators needs assessment scoring tool to derive the coverage and continuity benefits, we tested fixed values of the coverage benefit β_i from 0 to 700, in increments of 50. We observed that as β_i is increased the number of villages covered by the deployment of mobile clinics increases. However, the proportion of people visited at least once decreases as β_i increases. Our computational results show that a reasonable compromise between coverage and continuity is reached when $200 \leq \beta_i \leq 300$. We conducted sensitivity analyses on the number of mobile clinics, on the choice of marginal benefit function, and on the way to determine the number of individuals visited per route.

Our results show that increasing the available budget for mobile clinics, and thus the number of mobile clinics, allows to cover more villages and more clusters. On the other hand, decreasing the number of mobile clinics from the current number in the program (five) would significantly decrease geographical coverage. In addition, we show that the choice of marginal benefit function does not seem to have a significant impact on the proposed solution, and therefore solutions obtained with linear marginal benefits seem robust. Similarly, the different policies to determine the number of individuals visited per route have very limited impact on the performance of the deployment. Hence, an equal division between all villages is recommended and is simpler in practice.

This paper fills a gap in the literature. Solving this problem and analyzing performance indicators contributes to a better understanding of the impact of strategical and tactical decisions on the deployment of mobile clinics for humanitarian relief. Our study will serve as a guide for practitioners when deciding how to incorporate continuity and coverage for the deployment of mobile clinics. Also, our analyses aid practitioners in justifying the number of clinics on the deployment based on the impact it can have on the coverage and continuity offered to the beneficiaries. This study will help our collaborator, as well as practitioners in the field, better justify strategic decisions that impact the tactical planning of mobile clinic deployment.

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A Clusters

Considering the sparsity of our network and to determine the geographical coverage of our solutions, we implemented a k-means algorithm to cluster the villages based on their geographical coordinates (latitude and longitude). The algorithm randomly selects k villages as centroids and assigns each remaining village to its closest centroid. Once each village is assigned, the latitude and longitude coordinates of each cluster's centroid is computed as the mean of the latitude and longitude of its associated villages. Given the new centroids, the villages are reassigned to their closest centroid, and this process is repeated 300 times. For each value of k, we do this process 10 times, each time starting with a different centroid seed. We also use the elbow method to determine the most appropriate number of clusters for our data set. Figure 21 shows the obtained elbow graph with the sum of normalized square distances. We can see that when setting $k \geq 8$, this seems to represent a good value. After carefully considering the geography and to make sure to properly represent geographical coverage, we have selected 10 clusters.

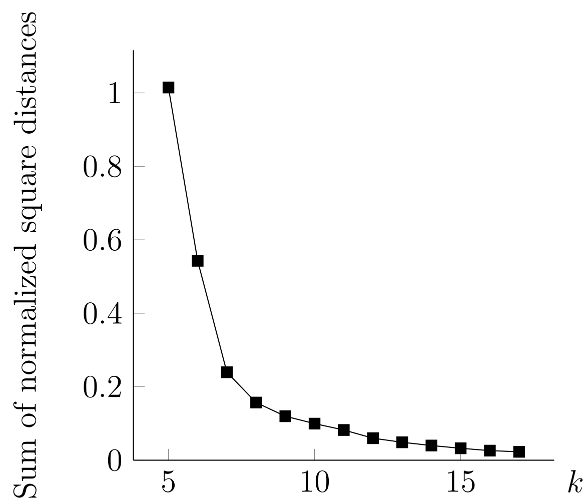

Figure 21: Elbow graph for k-means algorithm

B Detailed computational results

Table 5 contains the detailed computational results when fixing $m = 5$ and $B = 5000$ with equal division of population in routes, and for the three marginal benefit functions (linear, highly diminishing and smoothly diminishing). Then, for each marginal benefit function, we present: the optimal solution value (z^*); and the total computational time in seconds (*Sec.*). The results are presented for each value of β_i tested, i.e., between 0 and 700 with increments of 50. Note that when $\beta_i = 0$ and with linear marginal benefits, the obtained solution represents the one implemented by our partner. In addition, for a given marginal benefit function, because the value of $\beta_i^v, \forall i \in \mathcal{N}^c, v \in \mathcal{V}$ (i.e., the continuity benefit) remains constant, the increase in the objective function is expected. Finally, comparing the objective function between the different marginal benefit functions is not possible as the value of $\beta_i^v, \forall i \in \mathcal{N}^c, v \in \mathcal{V}$ varies according to each function.

Table 5: Detailed computational results $m = 5$, $B = 5000$ and equal division of population in routes

	Linear		Highly		Smoothly	
β_i	z^*	Sec.	z^*	Sec.	z^*	Sec.
0	108,250	128	279,851	62	186,117	1,821
50	109,104	21	280,776	74	186,992	84
100	110,166	14	281,776	187	187,967	107
150	111,316	95	282,801	45	189,075	17
200	112,562	189	283,927	128	190,235	263
250	113,932	248	285,127	70	191,435	35
300	115,589	55	286,327	75	192,635	1,114
350	117,596	390	287,571	75	193,927	437
400	119,742	216	288,821	73	195,277	143
450	121,942	60	290,071	114	196,665	4,769
500	124,142	230	291,339	47	198,151	1,208
550	126,342	193	292,739	31	199,831	165
600	128,542	274	294,139	113	201,649	731
650	130,742	158	295,539	124	203,639	70
700	132,942	167	297,001	99	205,683	242

Table 6 contains the detailed computational results when fixing $m = 5$ and $B = 5000$ with linear marginal benefits for *population proportion*, *score proportion*, *vulnerability proportion*, and *accessibility proportion*. Note that the results for *equal proportion* have been presented in Table 5. The first column contains the coverage benefit per location i (β_i). Then, for each way to divide the number of people in a route, we present: the optimal solution value (z^*); and the total computational time in seconds (*Sec.*).

Table 6: Detailed computational results $m = 5$, $B = 5000$, and linear marginal benefits

	Population		Score		Vulnerability		Accessibility	
β_i	z^*	Sec.	z^*	Sec.	z^*	Sec.	z^*	Sec.
0	108,250	26	108,250	27	108,250	27	108,250	206
50	109,119	14	109,102	64	109,100	91	109,103	101
100	110,193	69	110,204	27	110,199	21	110,210	29
150	111,343	73	111,354	18	111,349	64	111,360	51
200	112,591	170	112,644	44	112,627	148	112,606	152
250	113,933	236	114,009	22	114,047	125	113,991	125
300	115,483	132	115,676	117	115,762	149	115,682	34
350	117,372	112	117,663	82	117,860	139	117,672	160
400	119,415	119	119,784	42	120,054	49	119,795	183
450	121,590	63	121,984	99	122,260	94	121,995	166
500	123,790	54	124,184	177	124,460	166	124,195	152
550	125,990	111	126,384	79	126,660	114	126,395	206
600	128,190	28	128,584	147	128,854	153	128,595	47
650	130,390	133	130,784	260	131,060	109	130,795	43
700	132,590	68	132,984	93	133,260	32	132,995	171