CIRRELT

CIRRELT-2023-20

Multi-Period Location Routing: An Application to the Planning of Mobile Clinic Operations in Iraq

Rosemarie Santa González
Marilène Cherkesly
Teodor Gabriel Crainic
Marie-Ève Rancourt

June 2023

Bureau de Montréal
Université de Montréal
C.P. 6128, succ. Centre-Ville
Montréal (Québec) H3C 3J7
Tél : 1-514-343-7575
Télécopie : 1-514-343-7121

Bureau de Québec
Université Laval,
2325, rue de la Terrasse
Pavillon Palasis-Prince, local 2415
Québec (Québec) G1V 0A6
Tél : 1-418-656-2073
Télécopie : 1-418-656-2624

Multi-Period Location Routing: An Application to the Planning of Mobile Clinic Operations in Iraq

Rosemarie Santa González[1,2,3], Marilène Cherkesly[1,2,3], Teodor Gabriel Crainic[1,2,*], Marie-Ève Rancourt[1,4]

[1] Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT)

[2] Analytics, Operations, and Information Technologies Department, School of Management, Université du Québec à Montréal

[3] Group for Research in Decision Analysis (GERAD)

[4] Department of Logistics and Operations Management, HEC Montréal

Abstract. Health service access and delivery are hampered during humanitarian crises due to disrupted health systems, damaged infrastructure, and healthcare worker shortages, this particularly in conflict zones. Mobile clinics are a strategy used to reach populations cut off from local health services, and organizations commonly rely on them during relief and recovery humanitarian efforts to deliver primary healthcare. In this study, we present a multiperiod location-routing problem (MLRP) with benefits for the tactical planning of mobile clinic deployment. Our set-packing formulation was developed and solved as part of a collaboration with Première Urgence Internationale (PUI). The proposed model aims to select communities to be served and design routes to be performed such that health benefits, measured by means of coverage and continuity of care functions, are maximized throughout the planning horizon. Results are presented for an application based on PUI's operations in Iraq, including sensitivity analyses on the parameters used to model the healthcare benefits. Managerial insights on the impacts of organizational strategic and tactical decisions, such as the number of mobile clinics and the relative importance given to coverage and continuity of care, are presented.

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

Acknowledgements. We thank Première Urgence Internationale for their ongoing support and collaboration. Also, we would like to thank Alain Vaillancourt for reaching out. While working on this project, T.G. Crainic was Adjunct Professor with the Department of Computer Science and Operations Research, Université de Montréal. Teodor Gabriel Crainic, Marie-Ève Rancourt, and Marilène Cherkesly were funded by the Natural Sciences and Engineering Council of Canada (NSERC). Additionally, Marie-Ève Rancourt was funded by the Institute for Data Valorisation (IVADO). This research was also partially founded by the Centre de recherche sur l'intelligence² en gestion de systèmes complexes (CRI²GS) of the School of Management Sciences, UQAM. This support is gratefully acknowledged. Thanks are due to the reviewers for their valuable comments.

Results and views expressed in this publication are the sole responsibility of the authors and do not necessarily reflect those of CIRRELT.

Les résultats et opinions contenus dans cette publication ne reflètent pas nécessairement la position du CIRRELT et n'engagent pas sa responsabilité.

---

* Corresponding author: teodorgabriel.crainic@cirrelt.net

Dépôt légal – Bibliothèque et Archives nationales du Québec
Bibliothèque et Archives Canada, 2023

© Santa González, Cherkesly, Crainic, Rancourt and CIRRELT, 2023

1 Introduction

Humanitarian crises induce challenges for health service access and delivery, including disrupted systems, damaged infrastructure, sudden changes in the nature and extent of the disease burden, restricted access to services, displaced populations, and healthcare worker shortages (McGowan et al., 2020). Such challenges are exacerbated in conflict zones partly due to security issues threatening both the beneficiaries and healthcare workers. Humanitarian standards, e.g., the Sphere standards (Sphere Association, 2018), advocate that people should have access to safe and integrated quality healthcare, with at least 80% of the population accessing primary healthcare within one-hour walk from dwellings. However, between 37% and 61% of the population is estimated to be without access to essential health services in 2030 (United Nations, 2018). As part of the most recent Sustainable Development Goals, the United Nations (UN) pledged to "ensure healthy lives and promote well-being for all at all ages" (United Nations, 2022), but despite the progress made to improve health worldwide, the rate of improvement has slowed, especially during COVID-19 due to its threats to health and consequent overwhelmed health systems (United Nations, 2019). Outreach services, i.e., health services provided by health workers away from the locations where they are usually delivered (e.g., hospitals and health centers), are one of the possibilities to improve health access to populations living in underserved areas (de Roodenbeke et al., 2011). In areas affected by a disaster or a conflict, and in many remote rural areas, mobile clinics are one of the only outreach strategies to deliver healthcare services (Blackwell and Bosse, 2007; Du Mortier and Coninx, 2007; Fox-Rushby and Foord, 1996; Gibson et al., 2011).

Mobile clinics (*a.k.a.* mobile health units and mobile hospitals) are an intermittent modality used to provide ambulatory health services and improve access to the health system (Du Mortier and Coninx, 2007; McGowan et al., 2020). They consist of vehicles transporting equipment and healthcare providers who deliver health services at predetermined outreach posts (McGowan et al., 2020). They typically offer a combination of primary healthcare services, including preventive actions (e.g., vaccination, screening, and health education) and curative services (e.g., obstetric, medical, and mental health interventions). They allow for quick response and flexibility due to their ability to move (Wray et al., 1999), and they can be equipped to respond to different issues (Blackwell and Bosse, 2007). They can also be used to prevent hospitalizations (Guo et al., 2001). During crisis responses, the World Health Organization (WHO) and its implementing partners often resort to mobile clinics to reach isolated and vulnerable groups (World Health Organization, 2019), e.g., displaced population in Syria and Iraq (UNICEF, 2018; World Health Organization, 2018). Lately, mobile clinics have been used to reach COVID-19 vaccination goals in countries around the world, including Canada and the United States (CBC News, 2021; Hauser and Fremson, 2021). Despite the benefits of mobile clinics and their usage endorsement by governments and non-for-profit organizations during humanitarian crises, they involve several logistics challenges (e.g., limited resources and security issues) and are expensive to operate (ICRC, 2006). This motivates the need for the development of better analytical tools to facilitate the deployment and management of mobile clinics in the field, which is the aim of this study.

1.1 Context and problem description

This paper presents an optimization model and managerial insights to support mobile clinics deployments and utilization in the context of humanitarian relief. Although our contribution and methodology are of general applicability to capacitated mobile health units, it is inspired by a real application of a mobile clinic deployment in a conflict zone (Iraq). Indeed, the proposed approach is the result of a collaboration with Première Urgence Internationale (PUI), an international non-governmental organization (NGO), that provides relief response to the basic needs of populations affected by humanitarian crises around the world. PUI intervenes in Iraq by assisting vulnerable refugees, internally displaced people, and host communities to improve their access to primary healthcare services (e.g., vaccinations, disease screening, prenatal consultations, and curative care) through mobile clinics (PUI, 2016).

In situations of humanitarian crises, local authorities and the Ministry of Health often lack the means to meet needs in their countries. In such cases, humanitarian organizations should consider providing assistance directly to people with no access to healthcare services. When planning for such assistance programs, important strategic decisions have to be made by analyzing the political and health situations. These decisions imply determining which regions to cover (e.g., countries or districts), the type of healthcare services to offer, the most appropriate delivery mode (e.g., mobile clinics, material support, and training activities), the number of resources, and the time frame of the humanitarian operations. Note that such decisions often depend on the available funding. Once the decision of deploying mobile clinics in a specific region has been made at the strategic level, the routing and scheduling decisions must be made at the tactical level considering the allocated resources. This implies selecting the points of departure and arrival (i.e., depots), the specific locations to be visited (e.g., villages or communities), the frequency and the moments of the visits, and the number of people to serve at every location. Decisions such as patient prioritization and provided treatments are made at the operational level. In this study, we propose a tool to support decisions made at the tactical level given the outcome of the decisions made at the strategic level. Note that solving the tactical problem (i.e., the location-routing problem) allows us to evaluate important key performance indicators, such as healthcare benefits, which allows a rapid-analysis of the strategic decisions.

We model the tactical planning of mobile clinic deployment as a multiperiod location-routing problem (MLRP) with profits (Archetti et al., 2014), an extension of the location-routing problem (LRP) (Prodhon and Prins, 2014), which is well suited to capture the time dependency of mobile clinic operations and the fact that locations to visit and the number of people to serve have to be selected. Note that, the notion of profits is accounted for by considering healthcare benefits in this case. The multiple-period representation allows to capture the notion of continuity of care, whereas benefit-collection representation allows to select the patients to visit as the whole population cannot be covered due to limited resources. Solving the MLRP allows decision makers to select the locations, schedules, and routes of the mobile clinics (tactical decisions), and to evaluate the impact of the allocated budget and the number of mobile clinics (strategic decisions). The model also allows to evaluate the impact of the quantification of the benefits on the number of individuals served with the humanitarian healthcare services in each village (coverage) and their visit frequency (continuity of care).

1.2 Contributions and organization of this paper

With this paper, we aim to bridge the gap in the literature relative to the complexity of assessing the benefits of mobile clinic deployment for outreach humanitarian relief. First, we propose a new MLRP set-packing formulation, which seeks to maximize the total benefit (Rasmussen and Larsen, 2011) of providing healthcare services while taking into account a budget for the operational and logistics expenses. Second, we model this benefit by devising and considering measures of coverage and continuity of care, the latter through a function based on expert health and vulnerability assessment to properly and realistically evaluate the population's needs. Our model also allows to conduct sensitivity analyses to derive valuable managerial insights.

Accessing, processing, and analyzing data represents a contribution of our work. In the literature, many authors rely on secondary data or publicly available data (Kovacs et al., 2019) due to the lack of access to information about humanitarian field operations, especially in conflict zones (Lukosch and Comes, 2019). Moreover, 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 and Coninx, 2007; ICRC, 2006). To increase the quality and contributions of our work, we collaborated with PUI to define the relevant research questions and problem to address as well as to collect valuable field data as proposed by Gupta et al. (2019) and Kunz et al. (2017). We also benefit from data collected by PUI on the field, which comprises healthcare and demographics information of vulnerable populations. In this context, the main challenges consist of modeling and solving an applied problem arising when planning mobile clinic operations, as well as performing extensive sensitivity analyses to make appropriate recommendations rather than developing scalable algorithms. Still, our approach is sufficiently general to support any mobile clinic deployment even if our model has been tested on data of PUI's operations in Iraq.

The remainder of this paper is organized as follows. A literature review is presented in Section 2. 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 complex 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 in quantitative methods (Chiappetta Jabbour et al., 2019). Papers presenting quantitative-based applications often rely on one instance to extract meaningful insights and make valuable context-specific recommendations (e.g., Arnette and Zobel, 2019; Balcik et al., 2019; Charles et al., 2016; Dufour et al., 2018; Hodgson et al., 1998; Laporte et al., 2022).

In this section, we position our contributions in the literature. First, we discuss previous studies that propose mathematical models to tackle mobile clinic deployments. Second, we examine how coverage and continuity have been addressed in the literature. Third, we survey the literature related to routing problems with profit-maximization. Finally, we briefly present studies that formulate problems as location-routing problems in non-humanitarian and humanitarian contexts, as well as studies that consider multiperiod location routing problems.

2.1 Mobile clinics for non-humanitarian relief

Several healthcare services that can be provided by mobile clinics have been documented in the literature. They are used for screenings, prevention, and treatment of various diseases including otological (Lim et al., 2021), diabetic retinopathy (Bechange et al., 2021), autism spectrum disorder (Kamali et al., 2022), astigmatism (Hashemi et al., 2014), pediatric dental services (Dawkins et al., 2013; Murphy et al., 2000), sexually transmitted diseases (Ellen et al., 2003). Also, mobile clinic deployments have been deployed to offer family planning and women's reproductive healthcare services (Al-Attar et al., 2017; Jamir et al., 2013; Phillips et al., 2017). Deployments of mobile clinics have also been used to provide mental health services for refugees (Peritogiannis et al., 2022; Robinson and Segrott, 2002; Samakouri et al., 2022), underprivileged people (Collinson and Ward, 2010), and for addicts (Jamir et al., 2013). Authors have also highlighted the benefits of mobile clinics when targeting specific populations such as people living in disaster prone areas (Blackwell and Bosse, 2007), indigenous population (Beks et al., 2020), homeless (Whelan et al., 2010), elderly (Aljasir and Alghamdi, 2010), veterans (Wray et al., 1999), and drug addicts (Breve et al., 2022). The model proposed in this study is flexible and reproducible for any mobile clinic deployments, independent of the service offered.

2.2 OR/MS approaches to mobile clinics

To the best of our knowledge, three studies have proposed OR/MS approaches for mobile clinic deployment for humanitarian relief and none of them consider multiple periods as we do in this study. 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 them 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. Bayraktar et al. (2022) solve the multi-period mobile facility location with mobile demand (MM-FLP-MD) in the context of refugee migration. The objective function minimizes the travel and set up costs of mobile clinics throughout the planning horizon. They also include continuity by considering the frequency of services offered to the migrating group. They propose an adaptive large neighborhood search algorithm (ALNS) and present the results for instances derived from the Honduras migration caravan crisis in 2018.

Furthermore, two studies present OR/MS approaches to deliver healthcare services in rural areas using mobile clinics. First, Savaşer (2017) propose a periodic location routing problem (PLRP) formulation. 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 tests it on instances derived from a deployment of mobile clinics in Turkey. Second, Büsing et al. (2021) introduce a capacitated set-covering formulation.

They consider the uncertainty associated with patients that relocate to seek healthcare services. They use robust optimization and result to Benders decomposition and constraint generation. Their algorithm is tested on instances derived from a case in rural Germany.

Table 1 presents a summary of the reviewed literature related to OR/MS approaches applied in the context of mobile clinics. Our study is the first to propose a mathematical formulation that was developed in close collaboration with practitioners and that seeks to maximize the benefit offered to the population over multiple periods. Moreover, we explore the effect of planning mobile clinic deployments to offer individual continuity of care.

Table 1: Summary of OR/MS approaches to mobile clinics

	Problem modeled	**Solution methodology**	**Objective function**	**Instances**
Bayraktar et al. (2022)	MM-FLP-MD	Heuristic method	Min. travel and set up costs	Honduras
Büsing et al. (2021)	CTP	Exact method	Min. total cost	Rural Germany
Doerner et al. (2007)	CTP	Heuristic method	Min. beneficiaries travel time, total distance traveled and max. beneficiaries covered	Senegal
Hodgson et al. (1998)	CTP	Exact method	Min. beneficiaries travel time	Ghana
Savaşer (2017)	PLRP	Heuristic method	Min. travel distance	Turkey
This paper	MLRP	Exact method	Max. healthcare benefits	Iraq

2.3 Coverage and continuity of care

In this paper, we use a common OR/MS literature definition of coverage to represent the availability of healthcare services provided by mobile clinics to a location (i.e., a village in this case). Therefore, a location is covered if it is visited, which is often the case in location-routing problems (e.g., Drexl and Schneider, 2015), in healthcare (e.g., Bruni et al., 2006), and humanitarian logistics (e.g., Rancourt et al., 2015). Considering that travel time and physical barriers could negatively impact healthcare (Agyemang-Duah et al., 2019; Martin et al., 2002), it makes sense in this context that a location is covered only if a mobile clinic visits this location and not a neighborhood location as it is done in Burkart et al. (2017), Naji-Azimi et al. (2012), and Veenstra et al. (2018).

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 by Maarsingh et al. (2016), that is management (multidisciplinary and institutional coordination and coherency), informational (availability of previous information among different healthcare providers), and relational (relationship between the patient and one or more healthcare providers). Authors usually consider continuity of care as the ongoing care by the same healthcare practitioner to an individual (i.e., relational), and it is incorporated by minimizing the number of healthcare practitioners assigned to a patient over the planning horizon (Bowers et al., 2015; Milburn and Spicer, 2013; Nickel et al., 2012). 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 for continuity of care, 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 patient-healthcare practitioner relation, and thus continuity of care, whereas Cinar et al. (2021) 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 the continuity of care.

In this paper, we consider that a location is covered when it is visited but we present and justify a different continuity measure adapted to the case of humanitarian relief where continuity is modeled as the ability to provide follow-up healthcare services more than once to the population seeking services. We account for continuity when an individual is visited multiple times by the mobile clinics, and assess the value of continuity of care by testing functions with different patterns of the marginal benefits offered by additional visits (see sections 4.3.1 and 4.4.3). We define continuity of care as the ongoing care provided by mobile clinics to a group of individuals at a location, which allows for relational, informational, and management continuity to individuals in a location. In fact, our definition of continuity applies to the services offered by the humanitarian program (i.e., healthcare access through mobile clinics), and not to specific assignments of patients to practitioners, since this aspect of continuity would not be possible in the context of humanitarian operations, because they are not as personalized and rigorously documented as home care programs implemented in a stable environment.

2.4 Vehicle routing with profits

Vehicle routing problems (VRPs) have driven extensive research since its introduction in the scientific literature (Dantzig and Ramser, 1959), and its diverse applications have led to several problem variants considering different attributes, i.e., constraints, decision sets and objectives (Vidal et al., 2013, 2020). For recent literature reviews see Konstantakopoulos et al. (2022), Mor and Speranza (2022) and Vidal et al. (2020). The classic VRP entails the selection of a set of routes to serve a given set of customers (Irnich et al., 2014) while minimizing cost, whereas the VRP with profits entails the selection of customers to serve considering the costs and the profits associated with customers (Archetti et al., 2014). In the latter, two different decisions have to be taken: i) which customers to serve, and ii) how to cluster the customers to be served in different routes (if more than one) and order the visits in each route (Archetti et al., 2014). Our optimization problem shares similitudes with the VRP with profits. Indeed, we consider a 'profit value' assigned to locations that represents the healthcare benefit obtained by the visits in a location, and unvisited locations are allowed (Lee and Ahn, 2019). The VRP with profits has been extensively studied in the literature for various applications as illustrated by the surveys of Archetti et al. (2014), Feillet et al. (2005), and Vansteenwegen et al. (2011).

Three categories of the VRP with profits have been defined: the team orienteering problem (TOP) (Gunawan et al., 2016), the capacitated profitable tour problem, and the VRP with private fleet and common carrier (Vidal et al., 2016). The routing component of our study resembles the TOP where the goal is to maximize the total profit collected by a fleet of identical vehicles located at a depot, subjected to travel time or distance constraints (Vansteenwegen et al., 2011). Moreover, the routing component of our problem can be considered as an extension of the TOP that includes multiple periods and multiple depots. In the humanitarian literature, it is often the case that the objective is to maximize the covered demand (Besiou et al., 2018). One of our contributions is to test and propose new measures (i.e., objective functions) that are well adapted for the context of mobile health units with limited resources to address humanitarian needs. Additionally, we are the first to address an extension of the TOP that includes multiple periods and multiple depot selection in the context of healthcare

2.5 Location-routing problem

The LRP integrates vehicle-routing with facility-location decisions (Nagy and Salhi, 2007), as considering both decisions separately leads to sub-optimal decisions (Salhi and Rand, 1989). For literature reviews on the LRP please refer to Drexl and Schneider (2015) and Prodhon and Prins (2014). 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. (2013, 2014) while using exact separation procedures and column generation.

Many approaches related to location science have been proposed for the tactical planning phase of humanitarian relief. Some applications include the location of disaster relief distribution centers (Balcik and Beamon, 2008; Maliki et al., 2022), food distribution centers (Rancourt et al., 2015), temporary hubs for disasters (Stauffer et al., 2016), and collaborative distribution centers (Balcik et al., 2019; Rodríguez-Pereira et al., 2021). Similarly, many routing-based approaches have been proposed for humanitarian relief. Some applications include the delivery of medical and non-medical supplies (Balcik et al., 2008; Hamedi et al., 2012; Naji-Azimi et al., 2012; Parvin et al., 2018), and the evacuations after a disaster or crisis (Victoria et al., 2015). Nevertheless, the combination of location and routing decision is understudied in the humanitarian relief literature, and only two studies propose LRP in humanitarian relief. The first one is related to the selection of sites for needs assessment (see Balcik, 2017, for the selective assessment routing problem, SARP) and the second one focuses on the placement of refugee camps and delivery of public services (see Arslan et al., 2021, for the location and location-routing problem, LLRP).

This paper contributes the most to the literature related to healthcare routing problems. We are the first to propose a multi-period location-routing problem arising in the context of humanitarian relief. To position our paper, we first present related studies in healthcare location-routing problems for humanitarian relief and then in multiperiod location-routing. Table 2 summarizes the related work.

Table 2: Summary of the most related location-routing problem papers

	Problem modeled	**Solution methodology**	**Objective function**	**Instances**
Albareda-Sambola et al. (2012)	MLRPDS	Heuristic method	Min. total cost	Artificial
Cherkesly et al. (2019)	LRCP	Exact method	Min. total cost	Liberia
Moreno et al. (2016)	SFL-TP	Heuristic method	Min. total cost	Brazil
Tunalıoğlu et al. (2016)	MLRP	Heuristic method	Min. total cost	Turkey
Yi and Özdamar (2007)	LRP	Exact method	Min. unsatisfied demand	Turkey
This paper	MLRP	Exact method	Max. healthcare benefits	Iraq

2.5.1 Healthcare location-routing problems in humanitarian relief

Yi and Özdamar (2007) propose an LRP to support healthcare operations and evacuation after a humanitarian crisis. The allocation of medical personnel to medical centers and emergency units is taken as location decisions, whereas the commodities needed to provide healthcare are routed from distribution centers and wounded people are routed from affected areas. Cherkesly et al. (2019) propose a location-routing approach, coined as the location-routing covering problem (LRCP) 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 is modeled as routing decisions. In addition, a maximum coverage radius is imposed on community health workers. Our study considers multiple origin and destination depots in a location-routing setting, and is the first to adapt benefit maximization in the context of mobile clinic deployment.

2.5.2 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 in the previous periods will affect decisions in subsequent periods. Drexl and Schneider (2015) highlight 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 an MLRP with decoupled time scales (i.e., the multiperiod location-routing problem with decoupled time scales, MLRPDS), 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 an adaptive large neighborhood search metaheuristic. Finally, Moreno et al. (2016) introduce a multi-product multimodal stochastic MLRP, referred to as the stochastic facility location and transportation problem (SFL-TP), arising in emergency relief logistics. In their proposed model they seek to minimize the total expected costs. They propose a heuristic based on the decomposition of decision variables into discrete disjoint subsets by time periods, emergency scenarios, and stochastic stages, and solve each disjoint subproblem by relaxing all variables that are not in the subproblem. The authors test their algorithm on instances based on real and estimated data from the 2011 floods and mudslides in Brazil.

To the best of our knowledge, there are no MLRP applied to healthcare as the related literature is mainly of methodological nature (Drexl and Schneider, 2015). Nagy and Salhi (2007) note that only one fifth of the LRP literature is application oriented and Prodhon and Prins (2014) call for further developments and more realistic MLRPs. By modeling the tactical planning phase as a MLRP, this paper is the first to model the multiperiod nature of mobile clinic deployments and to consider both location and routing decisions. To the best of our knowledge, this is also the first study to use real data provided and gathered by field practitioners in a conflict zone. These data are used to formulate and validate the model.

3 Problem definition and mathematical formulation

In this section, we first discuss the MLRP arising in the context of mobile clinics in an underserved area. Then, we present the notation and formulate the problem with a set-packing formulation. Finally, we provide the algorithm used to generate the routes in our formulation.

3.1 The MLRP for mobile clinics deployment

When using mobile clinics to alleviate the deficit of healthcare during humanitarian crises, due to limited available resources and the fact that they are temporary and not as personalized as permanent health services, the objective is different. Indeed, the health benefits (i.e., coverage and continuity of care) must be maximized as opposed to imposing service levels as lower bounds. In this study, a set of locations in need of healthcare have been already targeted and assessed by humanitarian field workers. However, only a subset of these villages can be served and have to be selected, and the results of a needs assessment will allow to determine representative values of the benefits based on the vulnerability of the targeted villages.

In the MLRP for mobile clinics deployment, a homogeneous fleet of mobile clinics is available at each time period of the schedule length and must depart from and return to a set of potential depots (selected in the first period) while serving the population in the set of covered villages. Potential depots include permanent healthcare facilities and warehouses that can securely hold medical equipment. They also have a fixed opening cost which is homogeneous and remains unchanged throughout the schedule length. Each route must respect a capacity (i.e., maximum number of patients served per time period) and not exceed the maximum travel time. Given the size of the fleet and the capacity of the mobile clinics, not all villages can be covered. Serving patients in a village also requires time to coordinate the visits, which is represented by a fixed coverage cost. In addition, covering each village is associated with a benefit (COV benefit). The number of visits (treatments) each patient receives in a covered village is associated with a continuity benefit (CNT benefit). We assume that to visit patients an additional time v in a covered village, each patient in the village must have already been treated $v-1$ times. Therefore, the number of visits each patient receives is a lower bound on the real number of visits patients could receive as patient prioritization may vary in practice. Note that the number of visits to a village is not equivalent to the number of visits (treatments) each person receives at a village and that the latter is associated with the CNT benefit. Moreover, because medical consultations require dedicated time from the village, a minimal number of days between visits to each village is imposed, which is denoted as a number of resting periods. This number of resting periods allows for the population to schedule other activities, while not hindering patients that need follow-up consultations. Finally, a maximal budget is available over our schedule length to cover the fixed costs to open depots and to cover villages, as well as the variable routing costs.

3.2 Notation and mathematical model

In the following, we present the notation as well as the mathematical model for the MLRP. Table 3 presents a summary of the sets, parameters, and decision variables used in our mathematical model.

Table 3: Mathematical notation

Sets	
$\mathcal{N}^e$	Set of depots
$\mathcal{N}^c$	Set of villages to cover
$\mathcal{A}$	Set of arcs
$\mathcal{V}$	Set of visit frequencies (number of times a patient may be served)
$\mathcal{T}$	Set of successive time periods
$\mathcal{R}$	Set of feasible routes
$\mathcal{R}^t$	Set of feasible routes at time period $t \in \mathcal{T}$
Parameters	
p_i	Population at village $i \in \mathcal{N}^c$
c_e	Fixed cost of operating a depot $i \in \mathcal{N}^e$
c_c	Fixed cost of covering a village $i \in \mathcal{N}^c$
β_i	Coverage benefit (COV benefit) associated with covering village $i \in \mathcal{N}^c$
β_i^v	Continuity benefit (CNT benefit) associated with serving a patient at village $i \in \mathcal{N}^c$ exactly $v \in \mathcal{V}$ times
d_{ij}	Distance of arc $(i, j) \in \mathcal{A}$
m	Number of available mobile clinics
Q	Capacity of a mobile clinic (number of patients that can be served in a time period)
B	Budget available for deployment
η	Number of resting periods between visits to each village
a_{ir}	Binary parameter equal to one if route $r \in \mathcal{R}$ visits node $i \in \mathcal{N}^e \cup \mathcal{N}^c$, zero otherwise
θ	Setup time at village $i \in \mathcal{N}^c$
γ	Time to serve a patient
δ	Maximum duration of a route
G_{ir}	Patients served at location $i \in \mathcal{N}^c$ with route $r \in \mathcal{R}$
c_r	Routing costs of route $r \in \mathcal{R}$
Decision Variables	
x_i	Binary variable equal to one if village $i \in \mathcal{N}^c$ is covered, zero otherwise
y_i	Binary variable equal to one if depot $i \in \mathcal{N}^e$ is selected, zero otherwise
λ_r^t	Binary variable equal to one if route $r \in \mathcal{R}^t, \forall t \in \mathcal{T}$, is selected, zero otherwise
ω_i^v	Binary variable equal to one if all the population at location $i \in \mathcal{N}^c$ has been served at least v times, zero otherwise
π_i^v	Continuous variable defined between zero and one that indicates the percentage of patients served at village $i \in \mathcal{N}^c$ at least v times

The MLRP for mobile clinics deployment 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 cover, 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 $i \in \mathcal{N}^e$ is given by c_e, and the fixed cost of covering a village $i \in \mathcal{N}^c$ is given by c_c. Let $\mathcal{V} = \{1, ..., |\mathcal{V}|\}$ be the set of visit frequencies, i.e., the number of times a patient may be served in a village, where $|\mathcal{V}|$ represents the maximum number of times a patient can be served (maximum number of treatments). The benefit is composed of a COV benefit β_i, associated with covering village $i \in \mathcal{N}^c$, and of a CNT benefit β_i^v associated with serving a patient $v \in \mathcal{V}$ times at village i. More details on the calibration of these parameters are provided in Section 4.3.1 and 4.4.1 for β_i and in sections 4.4.3 for β_i^v. The arc set represents the shortest paths between two nodes and is defined as $\mathcal{A} = \{(i,j) : \{i, j \in \mathcal{N}^e \cup \mathcal{N}^c\}\}$, where each arc $(i,j) \in \mathcal{A}$ is associated with its 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 must serve in a time period. Let $\mathcal{T}$ be the set of successive time periods making up the schedule length that is repeated along 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 $(i_1, i_2, ..., i_{n-1}, i_n)$, $i_k \in \mathcal{N}^e \cup \mathcal{N}^c, k = 1, \ldots, n$. Routes start and end at a depot, i.e., $i_1, i_n \in \mathcal{N}^e$, and serve patients in a subset of villages $\{i_2, \ldots, i_{n-1}\} \in \mathcal{N}^c$. The total number of patients treated on each route is Q, and the number of patients treated at each node (i.e., villages), G_{ir}, is determined depending on different policies (see sections 4.3.1 and B). Each route $r \in \mathcal{R}$ is 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 ($\theta > 0$), and the patient service time in each village (γ is the time to serve a patient), and which respects the maximum duration allowed δ. Routes are further characterized by a cost, c_r, representing the routing costs. The algorithm implemented to generate routes in this study is detailed in Section 3.3.

The MLRP is formulated as a set-packing formulation that seeks to maximize the total benefit under a budget and several routing constraints. To formulate the problem, we use binary variables x_i equal to one if village $i \in \mathcal{N}^c$ is covered (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 served at least v times. The formulation also uses continuous variables π_i^v defined between zero and one that indicates the percentage of patients served at village $i \in \mathcal{N}^c$ at least v times. The MLRP can then be modeled as follows.

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

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

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

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

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

$$x_i \leq \sum_{t\in\mathcal{T}}\sum_{r\in\mathcal{R}^t} a_{ir}\lambda_r^t \quad \forall i \in \mathcal{N}^c, \tag{6}$$

$$\pi_i^v \leq x_i \quad \forall i \in \mathcal{N}^c, \quad v = 1, \tag{7}$$

$$\sum_{r\in\mathcal{R}^t} a_{ir}\lambda_r^t + \sum_{t'=t+1}^{t'\leq t+\eta}\sum_{r\in\mathcal{R}^{t'}} a_{ir}\lambda_r^{t+1} \leq 1 \quad \forall i \in \mathcal{N}^c, \quad t \in \mathcal{T}, \quad t \leq |\mathcal{T}|-1, \tag{8}$$

$$\frac{\sum_{t\in\mathcal{T}}\sum_{r\in\mathcal{R}^t} G_{ir}\lambda_r^t}{p_i} \geq \sum_{v\in\mathcal{V}} \pi_i^v \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}, \tag{9}$$

$$\pi_i^v \geq \omega_i^v \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}, \tag{10}$$

$$\omega_i^v \geq \pi_i^{v+1} \quad \forall i \in \mathcal{N}^c, \quad v \leq |\mathcal{V}|-1, \tag{11}$$

$$x_i \in \{0,1\} \quad \forall i \in \mathcal{N}^c, \tag{12}$$

$$\pi_i^v \geq 0 \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}, \tag{13}$$

$$\pi_i^v \leq 1 \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}, \tag{14}$$

$$y_i \in \{0,1\} \quad \forall i \in \mathcal{N}^e, \tag{15}$$

$$\lambda_r^t \in \{0,1\} \quad \forall r \in \mathcal{R}^t, \quad t \in \mathcal{T}, \tag{16}$$

$$\omega_i^v \in \{0,1\} \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}. \tag{17}$$

The objective function (1) maximizes the total benefit computed as the sum of the COV and CNT benefits. Note that β_i and β_i^v are measured per village, which allows for a unified measure of the total healthcare benefit. In fact, the first term of the objective function allows to compute the total COV benefit by multiplying β_i with a binary variable indicating if the village is covered or not, whereas the second term of the objective function allows to compute the total CNT benefit by multiplying β_i^v with the percentage of the population served per village. In Section 4.3, we explain how the beta coefficients are computed to reflect the population vulnerability. Constraint (2) imposes the budget available for the deployment during the schedule length, i.e., the budget allowed to cover the costs of opening and maintaining depots, of covering villages, and routing costs. Constraints (3) ensure that no more than the maximal 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. Therefore, vehicles can depart only from depots opened at the beginning of the schedule length, i.e., at $t = 0$. 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 villages can only be covered if they are visited in a selected route. Constraints (7) impose that patients can only be served in covered villages, i.e., a mobile clinic may not cover a village without providing visits to patients in the given village. Constraints (8) ensure that there are η resting periods between visits to each village, i.e., a subsequent visit to a village can only occur if it is at least η periods after the last visit. Constraints (9) link the route variables with the percentage of the population served v times. Constraints (10) and (11) ensure that patients can be served v times only if all patients in that village are served $v - 1$ times, e.g., no patient will receive a second visit until all the demand for a first visit is satisfied at the village. Constraints (12)–(17) define the variable domain.

3.3 Route generation algorithm

Algorithm 1 details how the set of routes is generated a priori as input for solving the MLRP. First, we provide the information needed for the algorithm to generate feasible routes. Second, we define the parameters used in the generation of the routes (lines 1–7) and initialize their values (lines 8–11). Note that we compute the maximum number of villages that can be visited in a route as follows

$$\bar{\nu} = \lfloor (\delta - 50\gamma)/\theta \rfloor,$$

which is a lower bound of the total potential remaining time for travel and setups at villages given that 50 patients are served (i.e, $\delta - 50\gamma$) divided by the setup time required per village ($\theta > 0$). Then, we generate all possible routes r that start at depot $e_1 \in \mathcal{N}^e$ and end at depot $e_2 \in \mathcal{N}^e$ (lines 12–27). The sets of each route are initialized and its corresponding parameters are computed (lines 16–21). The total duration of the route is computed as the setup time for each covered village, the service time for the 50 visited patients, and the travel time which is a linear function of the distance traveled. The cost of the route is computed as a linear function of the distance. The number of patients served at each location is computed according the different rules proposed in Appendix B. Finally, if the total duration of the route r respects the maximum route duration δ, the route is added to the set of feasible routes $\mathcal{R}$ (lines 22–23).

Algorithm 1 Generation of the set $\mathcal{R}$ of feasible routes

Require: $\mathcal{N}^e, \mathcal{N}^c, \mathcal{A}, d_{ij}, \theta, \gamma, \delta$

Define $\mathcal{N}_r$ as set of stops (depots and covered villages) in route $r \in \mathcal{R}$
Define $\mathcal{A}_r$ as set of arcs in route $r \in \mathcal{R}$
Define T_r as the total duration of route $r \in \mathcal{R}$
Define c_r as the cost per route $r \in \mathcal{R}$
Define κ as the cost per unit of distance
Define ψ as the time (in minutes) per unit of distance
Define $\bar{\nu}$ as the maximum number of villages that can be visited in a route
Initialize $N_r \leftarrow 0, T_r \leftarrow 0, c_r \leftarrow 0$
Initialize $a_{ir} \leftarrow 0, i \in \mathcal{N}^e \cup \mathcal{N}^c$
Initialize $G_{ir} \leftarrow 0, i \in \mathcal{N}^c$
Initialize $\bar{\nu} \leftarrow \lfloor (\delta - 50\gamma)/\theta \rfloor$
for $e_1 \in \mathcal{N}^e$ **do**
    for $e_2 \in \mathcal{N}^e$ **do**
        for $\nu = 0$ to $\bar{\nu}$ **do**
            Generate all possible routes r
            $\mathcal{N}_r = (e_1, i_1, ..., i_\nu, e_2), i_1, ..., i_\nu \in \mathcal{N}^c, i_k \neq i_l (1 \leq k \leq \nu, 1 \leq l \leq \nu), \nu = |N_r| - 2$
            $\mathcal{A}_r = \{(e_1, i_1), (i_\nu, e_2)\} \cup \{(i_k, i_{k+1}) \text{ s.t. } 1 \leq k \leq \nu\}$
            $a_{ir} = 1, i \in N_r$
            $T_r = \theta(|\mathcal{N}_r| - 2) + 50\gamma + \sum_{(i,j) \in \mathcal{A}_r} \psi d_{ij}$
            $c_r = \sum_{(i,j) \in \mathcal{A}_r} \kappa d_{ij}$
            Compute $G_{ir}, i \in \mathcal{N}_r \cap \mathcal{N}^c$ according to capacity division (see Section B)
            if $T_r \leq \delta$ **then**
                $\mathcal{R} \leftarrow r$
            end if
        end for
    end for
end for

4 Computational results

In this section, we present the results of the numerical experiments and sensitivity analyses conducted based on humanitarian operational information provided by PUI and the outputs of an in-depth population need assessment. Indeed, to ensure realism and relevance, the experiments were conducted on data from a primary healthcare program undertaken by our partner in Iraq. Moreover, we evaluate the impact of considering coverage and continuity of care within the methodology proposed for the deployment of mobile clinics as well as the impact of strategic decisions (i.e., the allocated number of mobile clinics and budget) and different tactical decisions (e.g., the relative importance given to coverage and some routing policies). 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.

The characteristics of the Iraq network are presented in Section 4.1, and Section 4.2 describes the proposed performance indicators to evaluate the healthcare benefits as well as the logistics performance in the context of mobile clinic deployment. The parameters and the solution for the current program implemented by our partner are presented in Section 4.3. The results of the sensitivity analyses are presented in Section 4.4.

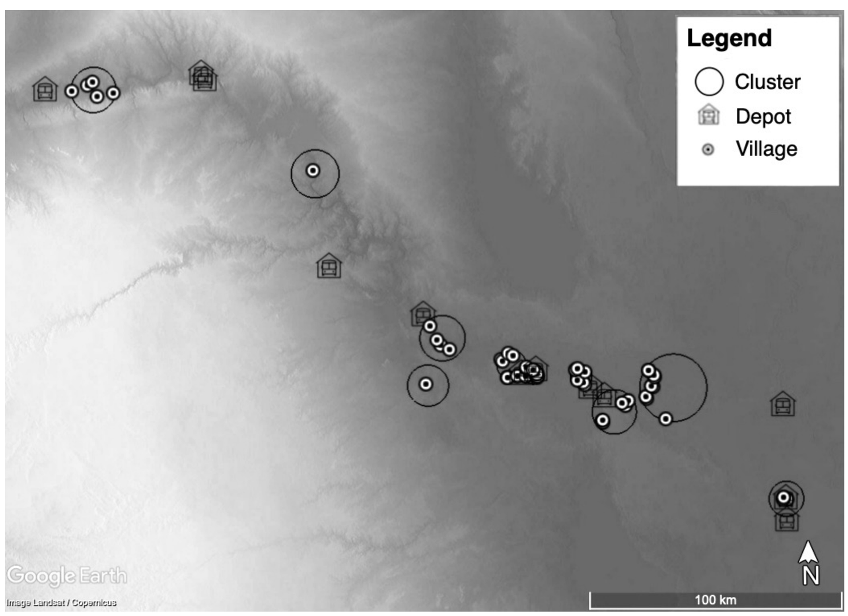


Figure 1: Location of potential depots and the villages to cover

4.1 Characteristics of the network and needs assessment

Our problem was defined through an ongoing collaboration with PUI, and the data for testing the proposed model and analyzing the *base case*, which represents the solution obtained under the current program policies, was derived from a deployment in Iraq consisting of 50 villages and 12 potential depots (see Figure 1). In Figure 1, we can notice that the network is relatively sparse with some clustered villages along few roads. This is common in humanitarian aid and development programs (e.g., Cherkesly et al., 2019; Dufour et al., 2018; Rancourt et al., 2015; VonAchen et al., 2016) and our methodology could be applied to such contexts. Note that the topology of the network makes it easier to generate all possible non-dominated routes than it would be in a dense and urban-like network because it is quite sparse. Moreover, the potential depot locations need to be accessible and secure for the personnel as well as the medical equipment. Therefore, 12 potential locations that have the required characteristics were identified, namely airports, operational hospitals, and governmental facilities. Bing Maps Distance Matrix API was used to compute the shortest path between every pair of nodes, such that $d_{ij}, \forall (i,j) \in \mathcal{A}$ represents the distance in kilometers within our area of interest's road network. Descriptive Statistics, minimal (Min), maximal (Max), average (Average), and standard deviation (St. dev.), on road distances between villages as well as between potential depots and villages are presented in Table 4. The area that PUI aims to cover is vast as the maximum distance between any two villages is around 414 km. However, in Figure 1 one can observe that some villages are near one another forming a total of 9 groups of villages (i.e., clusters), and every cluster but one has at least one potential depot close by and there are four more isolated depots that are located between some clusters.

Table 4: 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
Potential 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 personnel, supported by logistics personnel, conducts an onsite needs assessment in each village once every three months. During these assessments, the team visits all villages and their nearest healthcare facility and interviews the village leaders as well as a few people representing the population (at least two women and two men) to gather pertinent information to evaluate healthcare needs in every targeted village in the area where the mobile clinic program will be deployed (i.e., a sample of the village representing the population). This information is compiled by the team into a report that is further analyzed at the end of the process, which lasts a few weeks. This assessment registers the estimated population seeking healthcare p_i and its demographics, the presence of vulnerable groups (e.g., pregnant women, children, and elderly), the presence of chronic diseases, the access to vital resources (e.g., food and water), the presence and type of humanitarian relief or aid distributed in the area by different organizations, the conditions of the permanent infrastructure and shelters, the livelihood (e.g., income and hygiene), the health access and the health concerns. Such valuable data can only be obtained with in-person visits to each village by medical and logistics practitioners. After each assessment, the collected data is then translated into different scores using an in-house tool developed by healthcare professionals. Using this tool, the information was converted to a total weighted health score for every village which assesses healthcare needs and is denoted by $s_i, \forall i \in \mathcal{N}^c$. Figures 2 and 3 present the characteristics of the villages, that is, their population and their health score. While the average population per village is of 1,640, we can notice that 41 villages (out of 50) have a population between 0 and 2,000. Therefore, while there are a few outliers, the villages are similar in terms of size. In terms of health score, the trend seems to follow a normal distribution with an average of 29,500, and 32 villages (out of 50) have a health score between 27,500 and 32,500. The data does not show a trend between the size and the health score of the villages. Due to confidentiality and security reasons, we can only report aggregated values and cannot report detailed information pertaining to the specific needs assessment data.

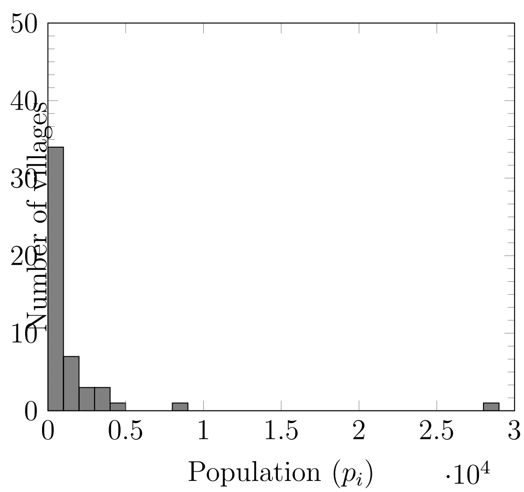


Figure 2: Population of the villages

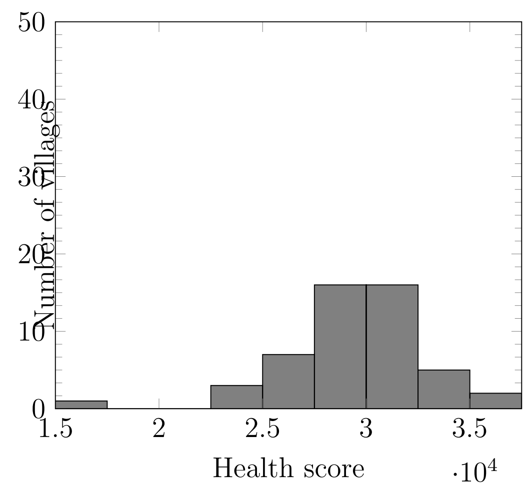


Figure 3: Health score of the villages

4.2 Performance indicators

We propose seven performance indicators to analyze the results obtained for planning mobile clinics deployments. These performance indicators are grouped in two categories, i.e., healthcare indicators and logistics indicators, and defined in Table 5. We measure the performance associated with healthcare services by computing the number of covered villages as well as the percentage of patients served at least v times in covered villages. We have also computed the number of patients served at least v times, but this indicator did not yield interesting insights. This will be discussed in further detail in the following subsections. The logistics performance is measured with five indicators. We report the total cost as well as the percentage of this cost associated with 1) location costs (opening and maintaining depots, and covering villages), and 2) routing costs. We also measure depot usage by considering their selection and routing frequencies. The selection frequency is computed as the number of times each depot is opened, whereas the routing frequency is computed as the number of routes departing and returning to each depot.

Table 5: Performance indicators

Name	Description
Healthcare indicators	
COV-V	Number of covered villages
CNT-v	Percentage of patients served at least v times in covered villages ($v \geq 1$)
Logistics indicators	
Total cost	Total cost of opening and maintaining depots, covering villages and routing costs
Location costs	Total cost of opening and maintaining depots, and covering villages
Routing costs	Total routing costs
Depot selection frequency	Number of times each depot is opened
Depot routing frequency	Number of routes departing and returning to each depot

4.3 The *base case* representing the current solution

In this section, we describe the *base case* that is defined by setting the parameter values to those of our partner. Note that PUI does not use an optimization model to design their network instead, they do it by hand. Therefore, the *base case* reproduces the decision policies of our partner by using our optimization model. PUI confirmed that our *base case* solution made sense in practice although it may slightly vary from the one implemented on the field. By deriving the *base case* with the mathematical model, we can systematically evaluate the current strategical and tactical planning decisions and their impacts on the mobile clinic deployment of PUI in Iraq. More precisely, sensitivity analyses (Section 4.4) are conducted to understand the impact of strategic (number of mobile clinics) and tactical decisions (the importance given to COV and CNT benefits, and routing policies) on the healthcare and logistics performance. Data about humanitarian operations are scarce and difficult to access (Besiou et al., 2018), especially in war zones as it is sensitive information, and we are not aware of other papers that rely on such data.

4.3.1 Parameters of the *base case*

In terms of operations, a two-week (ten days, $|\mathcal{T}| = 10$) schedule length is repeated over two months, and the fleet is composed of five mobile clinics ($m = 5$). Each mobile clinic has a single doctor and must provide services each work day to exactly 50 patients ($Q = 50$). This capacity comes from service constraints imposed by our partner as well as the Ministry of Health. Our partner also imposes a two-day resting period ($\eta = 2$) between visits to a given village in their two-week schedule. A maximum budget of $5,000 for each two-week schedule length ($B = 5,000$) is available to cover routing costs, the costs of covering villages, and the costs of opening and maintaining depots. Moreover, if a mobile clinic visits more than one village, its capacity Q is divided equally according to the number of stops, denoted as the *equal proportion* capacity-allocation policy. For example, given $Q = 50$ and a route covering two villages, 25 patients will be served in each village. In practice, while the service time may vary for each patient, our partner highlighted that for planning mobile clinic routes homogeneity for the patient service time must be assumed. Therefore, PUI uses an average service time for each patient of five minutes ($\gamma = 5$) to plan and evaluate their program, as it allows to properly represent the total time spent at a village during a visit in practice. Given that each work day lasts six hours and that 50 patients must be served, 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. Finally, in the *base case*, our partner considers a subset of the regular routes which start and end at the same depot so that the healthcare team needs to get back to its origin depot at the end of the day for practical implications. A total of 2,711 different feasible non-dominated routes were generated, where $R^{t=1} = ... = R^{t=|T|}$.

After discussions with our partner, their COV benefit is implicitly set to $\beta_i = 0$. In fact, in their current program, they select a limited number of villages that have the highest weighted health score per population and provide them with the maximal number of visits during the schedule length. The maximal CNT benefit for a village corresponds to its health score extracted from the needs assessment (s_i) and is reached when all patients of that village are served the maximum number of times ($|\mathcal{V}|$). Therefore, the CNT benefit to serve all patients in village i v times is:

$$\beta_i^v = (\alpha_v - \alpha_{v-1})(s_i),$$

where the health score (s_i) is multiplied by the marginal value of serving all patients v times ($\alpha_v - \alpha_{v-1}$). Our partner considers all visits to a patient of equal importance (constant marginal value), therefore, α_v can be computed as follows:

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

The performance of the *base case* is presented in the following section, whereas the impacts of modifying this *base case* are presented in Section 4.4 to evaluate potential improvements of the current solution.

4.3.2 Analysis of the *base case*

The *base case* contains 27,572 variables and 326,501 constraints. Our method allows us to find a solution within 128 seconds. Table 6 presents the results obtained for the *base case*, i.e., the value of each performance indicator. We notice that with their current parameter setting, our partner can cover 15 villages out of 50 potential villages. In these covered villages, 69%, 15%, and 11% of the population is served at least once, twice, and thrice, respectively. This represents 2,208, 176, and 116 people served at least once, twice, and thrice. In addition, the total cost is $2,712, where 16% and 84% of this cost are for location and routing costs. Finally, five depots are opened (see Figure 4) and each depot is used exactly ten times.

Table 6: Results obtained for the *base case*

Performance indicator	Value
Healthcare indicators	
COV-V	15
CNT-1	69%
CNT-2	15%
CNT-3	11%
Logistics indicators	
Total cost	$2,712
Location costs	16%
Routing costs	84%

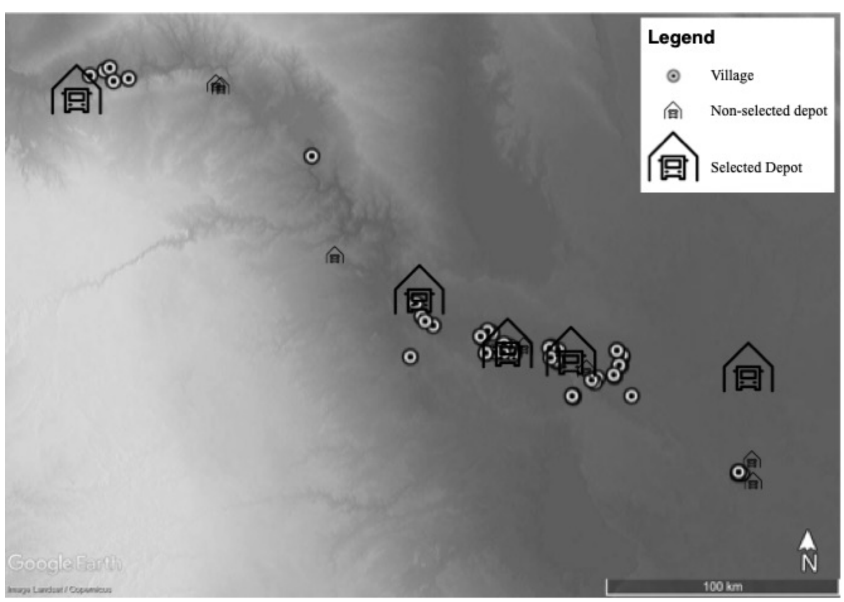


Figure 4: Selected depots for the *base case*

4.4 Sensitivity analyses

In this section, we use our mathematical model to systematically evaluate the effect of strategic and tactical decisions on the healthcare and logistics performance of mobile clinic deployment for humanitarian relief. The goal of these analyses is to validate the implicit parameters used by our partner and the robustness of the solutions relative to changes in their practice. Here, we present summarized results, and detailed computational results are reported in Appendix A.

First, we evaluate how the relative importance of coverage of care impacts healthcare and logistics performance. In this analysis, we test fixed values of β_i from 0 to 700, by increments of 50. Second, we investigate the impact of adding and removing mobile clinics. We present the results obtained with $\beta_i = \{0, 100, 200, 400\}$ for conciseness reasons as the other values did not yield further insights. Given that the number of mobile clinics depends on funding allocation decisions, this analysis allows for a discussion with our partner and its donors to better understand how the program could benefit from additional mobile clinics. For these analyses, we present the number of covered villages, the average proportion of the population served at least once, twice, and thrice in covered villages, the total cost, and its proportion associated with location and routing costs.

Moreover, using all the tested values of β_i (0 to 700, by increments of 50), we analyze how the marginal CNT benefit function impacts the performance indicators. For this analysis, we report the proportion of the total cost associated with the location and routing costs. For the other performance indicators (healthcare indicators and total cost), we compute the impact of the changes compared to the *base case* solution for the same value of β_i. That is, the impact on the number of covered villages is computed as (COV-V$_\xi$ − COV-V)/COV-V, where COV-V$_\xi$ is the number of covered villages for a given parameter setting ξ and COV-V is the number of covered villages for the *base case* with the same value of β_i. The impact on the percentage of patients served at least v times is computed as (CNT-v_ξ − CNT-v)/CNT-v, where CNT-v_ξ is the average proportion of population served at least v times ($v \geq 1$) for a given parameter setting ξ, and where CNT-v is the average proportion of population served at least v times for the *base case* with the same value of β_i. The impact on the total cost is computed as (TC$_\xi$ − TC)/TC, where TC$_\xi$ is the total cost for a given parameter setting ξ, and where TC is the total cost for the *base case* with the same value of β_i.

Finally, two sensitivity analyses on the structure of the routes are presented in Appendix. In Appendix B, we study the impacts of the computation of the number of visits in every village of a route on the solutions. In Appendix C, we analyze the effect of the choice of the origin and destination depots.

4.4.1 Relative importance of coverage of care

The relative importance of coverage of care was tested by modifying the value of β_i by using fixed values from 0 to 700, with increments of 50. These values were determined after conducting an initial analysis and were set to ensure that, at the lowest value, no weight was given to the COV benefit (i.e., $\beta_i = 0$), and there was a clear difference from one solution to another over the β_i increments. When increasing β_i, higher importance is given to coverage rather than continuity. The maximal value (i.e., $\beta_i = 700$) was set to ensure that the trend remained the same, i.e., that the marginal COV benefits remained null when increasing the value of β_i further. Let us also recall that the current COV benefit of our partner is set to $\beta_i = 0$. Therefore, our analysis allows us to find alternative solutions that offer a better compromise between coverage and continuity of care. All solutions were obtained between 14 to 390 seconds, with an average computational time of 163 seconds.

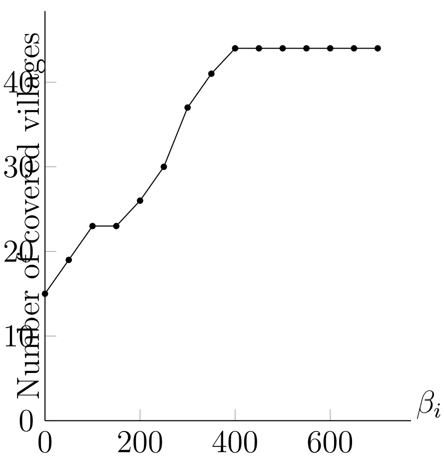


Figure 5: Number of covered villages

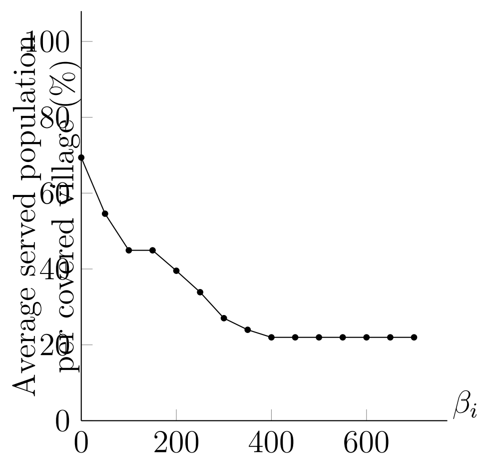


Figure 6: Average proportion of the population served at least **once**

First, we discuss the results relative to the healthcare performance, i.e., the number of covered villages and the average proportion of the population served at least v times (Figures 5–8). Compared with the *base case*, between 4 and 29 additional villages can be covered (i.e., a total between 19 and 44 villages out of 50 villages), and more villages are covered as the value of β_i increases. However, compared with the *base case* CNT-1, CNT-2, and CNT-3 decrease between 14% and 47%, 3% and 10%, and 2% and 7%, respectively. More precisely, the maximum number of covered villages is reached when $\beta_i \geq 400$, with 22%, 5%, and 4% of the population served at least once, twice, and thrice on average. In addition, most patients served twice are also visited thrice. As expected, increasing the value of β_i allows covering more villages while CNT-v decreases. Note that the number of patients served at least once and twice ranges between 2,198 and 2,210, and between 160 and 176 for all values of β_i. In addition, independently of the value of β_i, there are always 116 people that are served at least thrice. This can be explained by

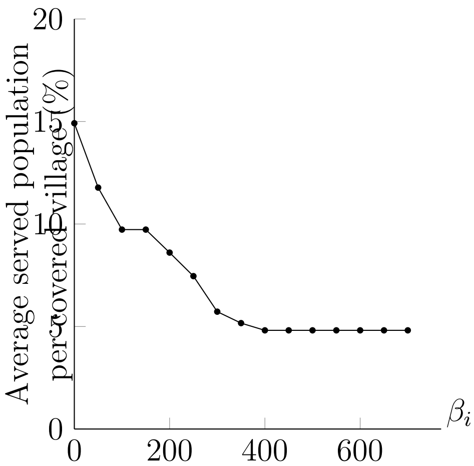


Figure 7: Average proportion of the population served at least **twice**

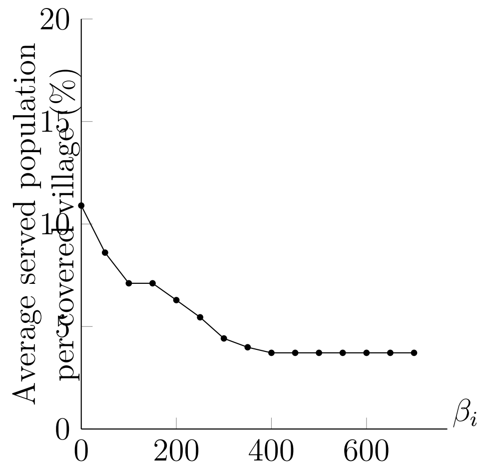


Figure 8: Average proportion of the population served at least **thrice**

the fact that the model maximizes the benefits and is constrained by limited resources (i.e., the capacity constraints on the number of people that can be served is restraining). On the other hand, because villages are similar in terms of population size, this implies that the proportion of the population served in the covered villages allows for comparison and is an appropriate indicator for continuity of care.

Second, we analyzed the logistics performance, i.e., the total cost and its percentage associated with location and routing costs, and the depot usage. Figure 9 shows the variation of the total cost according to the value of β_i. We can notice that the total cost ranges between \$2,420 ($\beta_i = 150$) and reaches up to \$2,946 ($\beta_i = 200$) without any specific trend with respect to the values of β_i, and more than 65% of this cost is associated with the routing costs. In general, we can observe that as the value of β_i increases, the total location costs tend to increase due to the increased number of covered villages whereas the routing costs decrease. Concerning the depot usage, Figure 11 shows the number of times each depot is selected, 15 being the maximum possible number as we tested 15 values of β_i. Independently on the value of β_i, there are either four or five open depots. When five depots are opened, each depot supports 10 routes, and when four depots are opened, three depots support 10 routes and one depot supports 20 routes. Three depots are opened 80% of the time over the tested values of β_i. Given the topology of the network, the location of the depots and their usage are not sensitive to a change in the relative importance of coverage of care.

Third, we estimate the trade-off between the benefits associated with coverage and continuity of care by analyzing the solutions obtained with different values of β_i. Figure 12 depicts a trade-off function where the x-axis represents the number of covered villages and the y-axis represents the average proportion of the population served at least once, twice and thrice. We notice that as the number of covered villages increases, the average

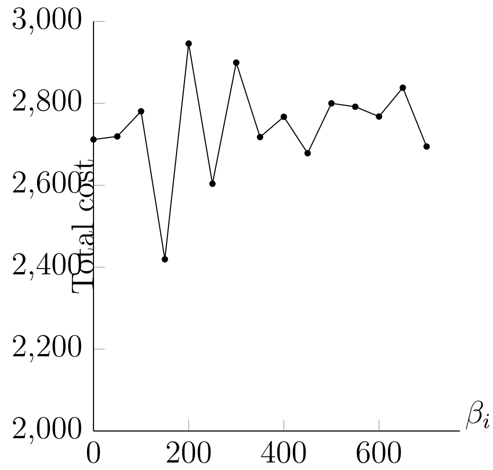


Figure 9: Total cost

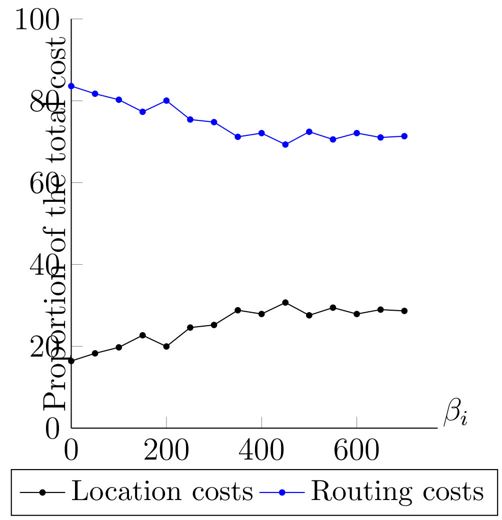


Figure 10: Proportion of the total cost associated with location and routing costs

proportion of the population served in these villages decreases exponentially. Note that the minimum and the maximum number of covered villages are 24 and 44. For every additional covered village between 15 and 23, the average proportion of the population served at least once, twice, and thrice decreases by an average of 2.6%, 0.5%, and 0.4%. These values correspond to the average marginal values and allow to estimate the trade-off between the benefits of coverage and continuity of care. For every additional covered

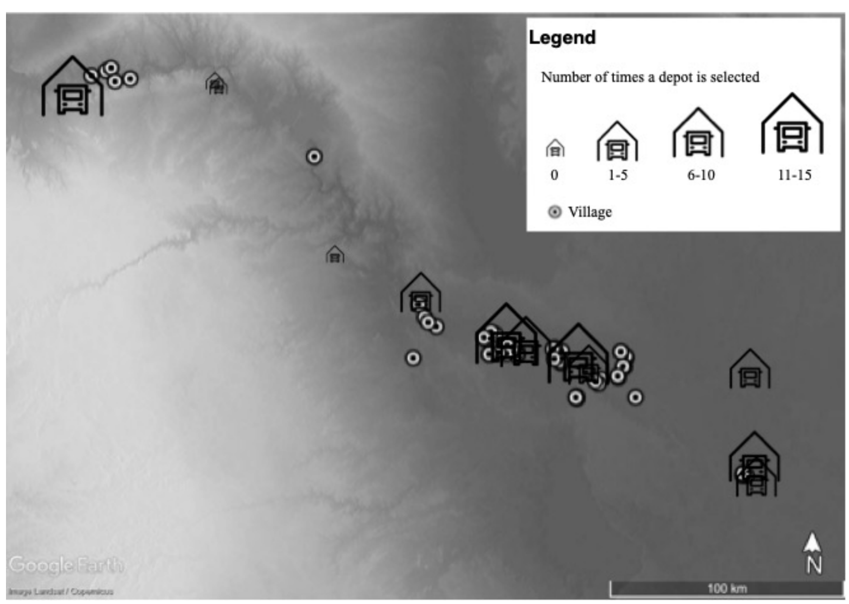


Figure 11: Statistics on selected depots related to coverage

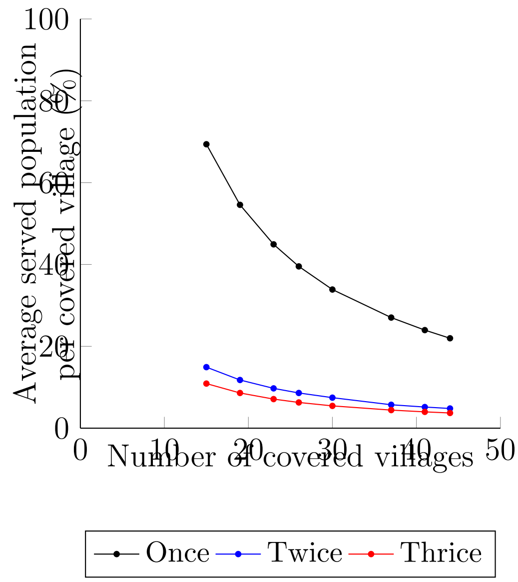


Figure 12: Average served population at least once, twice, and thrice per covered villages as a function of the number of covered villages

village between 23 and 30, these decreases are of 1.4%, 0.3%, and 0.2%. Finally, for every additional covered village between 30 and 44, these decreases are of 1.0%, 0.2%, and 0.2%. Therefore, the proportion of the population served at least twice and thrice decreased of less than 1% on average, and we can observe an important decrease in the population served at least once between 15 and 23 villages.

Our results show that a reasonable compromise between coverage and continuity of care 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 CNT-1, CNT-2, and CNT-3 vary from 27% to 40%, from 6% to 9%, and from 5% to 6%. On the other hand, the highest values of the total cost are obtained with $\beta_i = \{200, 300\}$, whereas the costs are the second lowest (i.e., \$2,604) with $\beta_i = 250$. Thus, we believe that a reasonable value would be $\beta_i = 250$ both in terms of healthcare and logistics performance to design the solution of our partner.

4.4.2 Impact of the number of mobile clinics

The impact of the number of mobile clinics on the performance of the system 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 used by our partner depends on funding allocation decisions made at the strategic level (i.e., in this case, $m = 5$), 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 this allows to understand the trends and the results. Other tested values of β_i do not provide additional information as the results remain stable. In addition, for this analysis, we do not present the maps of the depot usage given the large number of mobile clinics tested, but we discuss the results in the text. All solutions were obtained within 1,500 seconds, with an average of 35 seconds.

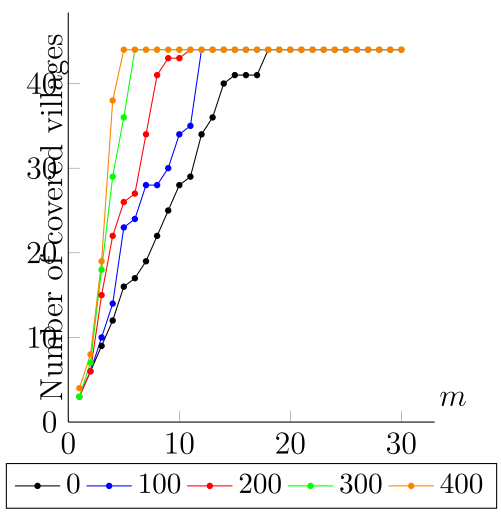


Figure 13: Number of covered villages ($B = \infty$)

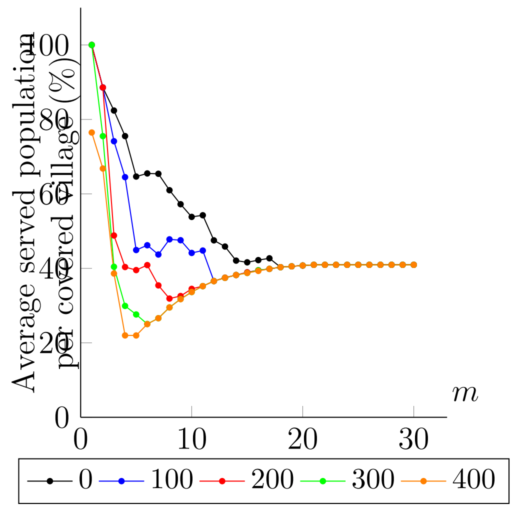


Figure 14: Average proportion of the population served at least **once** ($B = \infty$)

First, we analyzed the healthcare performance (Figures 13–16). 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 ($m = 5$), an increase of one mobile clinic allows covering one or two additional villages, while an increase of two mobile clinics has a higher impact on the number of covered villages, ranging from five villages to up to 20 additional villages. Removing mobile clinics on the other hand decreases COV-V, and at most ten villages are covered when $m \leq 3$. As the number of covered villages increases when increasing the number of mobile clinics, CNT-1, CNT-2, and CNT-3 decrease, but stabilize at around 40%, 6%, and 4% with at least 14 mobile clinics. This decrease does not imply that the number of patients decreases. On the contrary, when the number of mobile clinics increases, the total population served among all villages increases as more villages are visited. That is, for each additional mobile clinic, there is an average increase of 240, 5, and 2 people served at least once, twice, and thrice.

Second, we analyzed the logistics performance. Figure 17 reports the total cost which ranges from \$1,017 with one mobile clinic to \$6,899 with 30 mobile clinics on average.

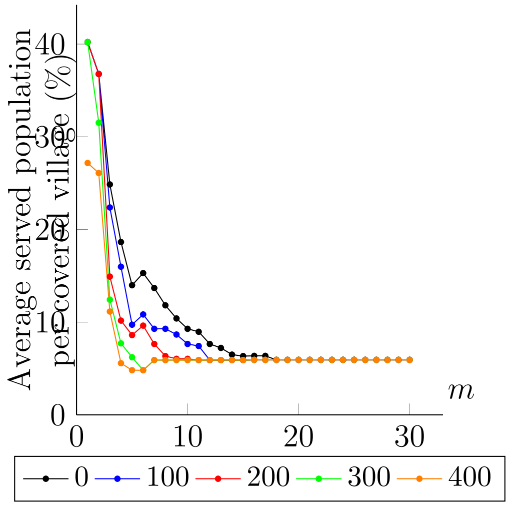


Figure 15: Average proportion of the population served at least **twice** ($B = \infty$)

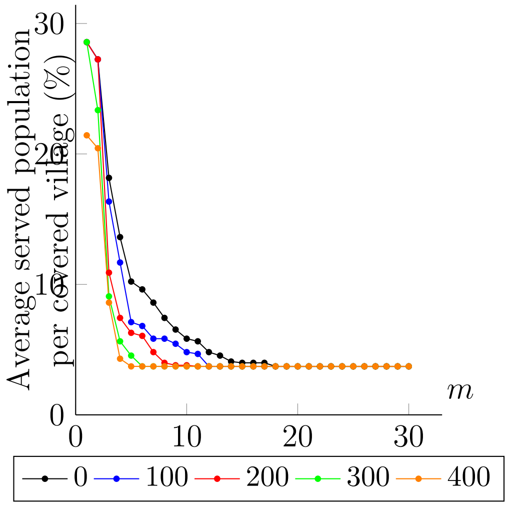


Figure 16: Average proportion of the population served at least **thrice** ($B = \infty$)

The trend shows an average increase of \$203 in the total cost as the number of mobile clinics increases, which can be explained by the cost of covering additional villages as well as the increased routing costs. In general, more than 70% of the total cost is associated with routing costs (see Figure 18), and with less than 10 mobile clinics, the proportion of the location costs rapidly increases and stabilizes at around 10 mobile clinics. This is explained by the increased number of covered villages for the first 10 mobile clinics (see Figure 13). When $1 \leq m \leq 6$, the number of opened depots is equal to the number of mobile clinics and the number of routes per opened depot is 10. The maximum number of opened depots, i.e., 11 out of 12 (one depot is never selected), is reached when there are at least 18 mobile clinics, and the average number of routes per depot is then 20.

Overall, this analysis shows that the number of covered villages increases with more mobile clinics, while CNT-1, CNT-2, and CNT-3 tend to decrease even though the number of visited patients increases. In terms of logistics performance, the total cost tends to increase linearly with the number of mobile clinics with a high percentage of this cost associated with routing costs. Increasing the number of mobile clinics also increases the number of opened depots as well as the number of routes per depot. Given the limited funding, it is not realistic to increase the number of mobile clinics by a large number, but the addition of one or two mobile clinics would allow for a significantly better coverage as well as provide more patients with second and third medical visits and, hence, allowing a reasonable continuity of care. However, decreasing the funding would worsen dramatically the potential impact of the program.

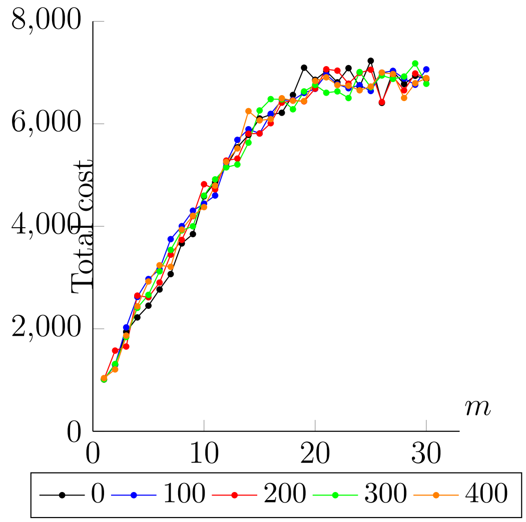


Figure 17: Total cost

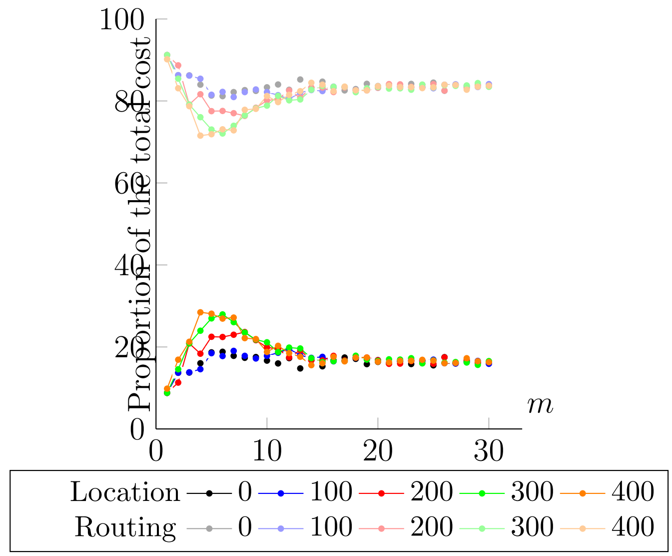


Figure 18: Proportion of the total cost associated with location and routing costs

4.4.3 Impact of the continuity of care benefit function

As indicated in Section 4.3, our partner evaluates the CNT benefit as an amount distributed equally over the number of visits (constant marginal CNT benefits), which can be modeled with a linear function. Such a function implies that all visits are of equal importance, while in practice, the first visit is often the most critical as it can help identify abnormalities (Bayliss, 1981). We thus aim to explore the impact of different CNT benefit functions, which give a larger benefit to the first visit relative to subsequent ones, on the performance of the network. 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.

We propose two alternative CNT benefit functions with user-defined parameters to capture *rapidly decreasing* and *slowly decreasing* marginal CNT benefits of an additional visit to a person. These functions are inspired by the economics theory of subjective value, also known as utility or marginal utility, where an individual's rational preference can be represented mathematically by a utility function (Baumol, 1972; Mas-Colell et al., 1995). For the continuity of care, a decreasing marginal utility is usually assumed (Dittmer, 2005). For example, a child in need of a one-dose vaccination has a decreasing marginal benefit relative to the continuity of care, since the first visit (when the shot is administered) is of greater importance than the subsequent follow-up visits. Let us recall that $\beta_i^v = (\alpha_v - \alpha_{v-1})s_i$, where $(\alpha_v - \alpha_{v-1})$ represents the marginal CNT benefit. With *rapidly decreasing* marginal CNT benefits, α_v is computed as

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

With *slowly decreasing* marginal CNT benefits, α_v is computed as

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

The values of a_h and a_s are set to impose higher importance on the first visit, and c is set to determine the rate at which the CNT benefit decreases. With rapidly decreasing marginal CNT benefits, the first visit has a weight of $a_h = 0.8$, and the remainder, i.e., 0.2, is distributed over the subsequent visits. With slowly decreasing marginal CNT benefits, the first visit has a weight of $a_s = 0.5$, which is lower than with rapidly decreasing marginal CNT benefits (i.e., $a_s \leq a_h$), thus allowing for a higher weight to 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 19 and 20 represent the value of α_v according to the choice of marginal CNT benefits obtained with two values of the maximal number of visits allowed, i.e., $|\mathcal{V}| = \{3, 5\}$.

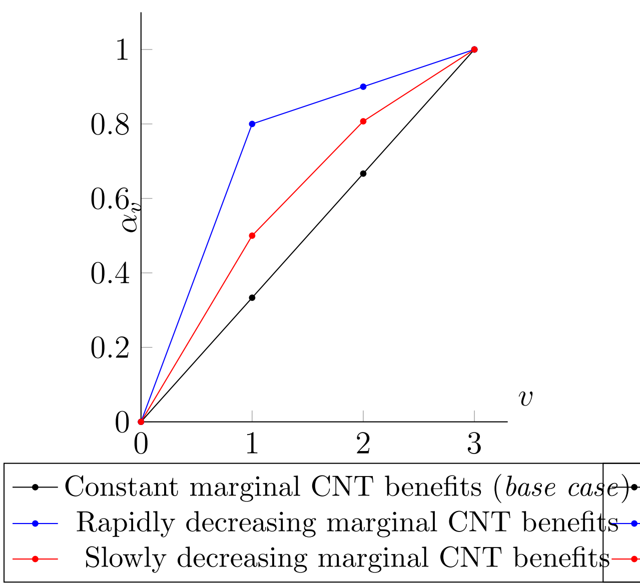


Figure 19: Value of α_v according to the marginal CNT benefit, $|\mathcal{V}| = 3$

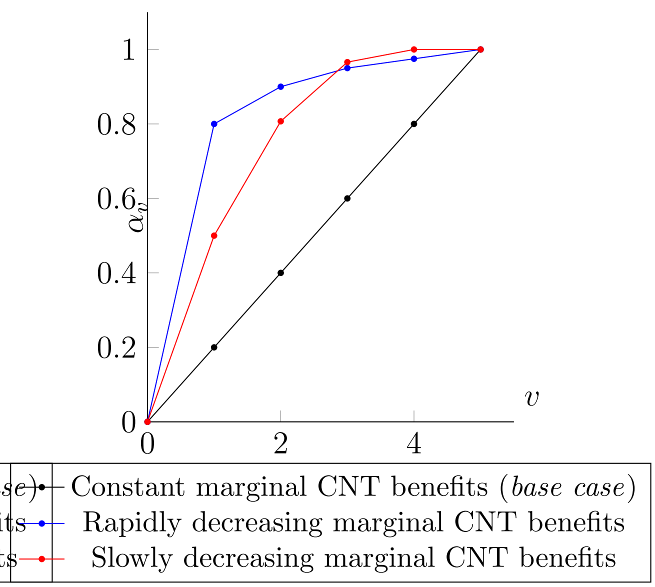


Figure 20: Value of α_v according to the marginal CNT benefit, $|\mathcal{V}| = 5$

First, we analyzed the performance associated with healthcare (Figures 21–22). Out of the 50 villages, the number of covered villages ranges from 18 to 30 and from 17 to 41,

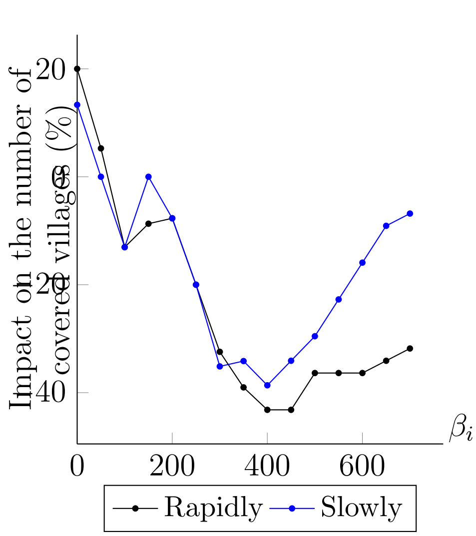


Figure 21: Impact on the number of covered villages when considering rapidly and slowly decreasing marginal CNT benefits ($m = 5$, $B = 5,000$)

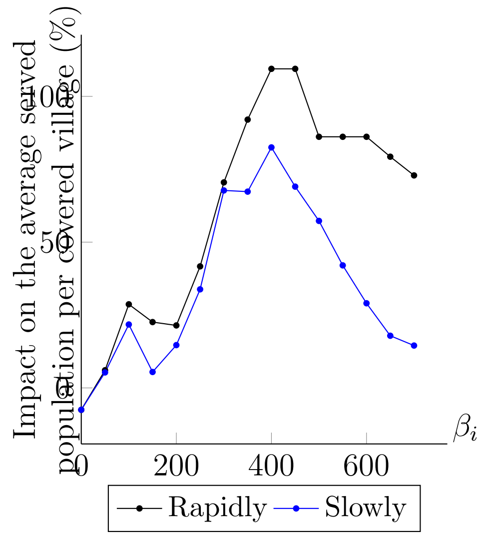


Figure 22: Average proportion of the population served at least **once** with rapidly and slowly decreasing marginal CNT benefits ($m = 5$, $B = 5,000$)

with rapidly decreasing and slowly decreasing marginal CNT benefits, respectively. When comparing the two new CNT benefit functions with the *base case* ($\beta_i = 0$ and constant marginal CNT benefits), three additional villages are covered with rapidly decreasing marginal CNT benefits, and two additional villages are covered with slowly decreasing marginal CNT benefits. Given this increase in the number of villages, CNT-1, CNT-2, and CNT-3 decrease. For both rapidly decreasing and slowly decreasing marginal CNT benefits, there is an impact of –8% and –8%, an impact of –95% and –17%, and an impact of –100% and –88% on CNT-1, CNT-2, and CNT-3. With $\beta_i = 0$ and rapidly decreasing marginal CNT benefits, patients are served at most twice. More generally, when $\beta_i \geq 100$, constant marginal CNT benefits provide better coverage of the villages. In addition, for both rapidly and slowly decreasing marginal CNT benefits, there is an increase on CNT-1, which can be explained by the lower number of covered villages. With slowly decreasing marginal CNT benefits, our results show an increase on CNT-2 when $\beta_i \geq 100$. The impact is at its highest when $\beta_i = 400$ since the number of covered villages is considerably lower, i.e., 27 covered villages with slowly decreasing marginal CNT benefits and 44 with constant marginal CNT benefits. With slowly decreasing marginal CNT benefits, there is a decrease of at least 75% on CNT-3, while with rapidly decreasing marginal CNT benefits, no one is covered thrice and there is a decrease of at least 95% on CNT-2. Therefore, compared to rapidly decreasing and slowly decreasing marginal CNT benefits, constant marginal CNT benefits offer better coverage of the villages as well as a better continuity of care since the proportion of the population served more than once increases.

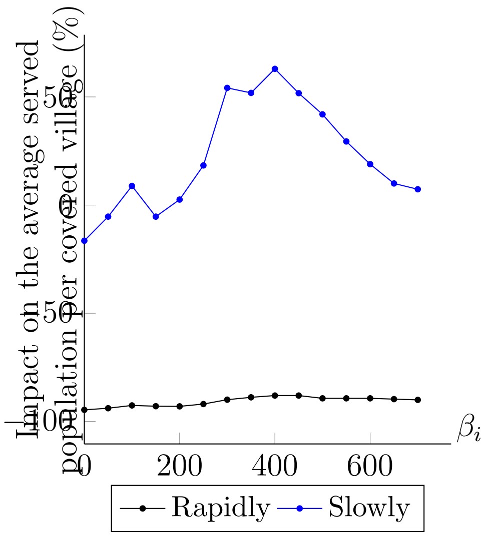


Figure 23: Average proportion of the population served at least **twice** with rapidly and slowly decreasing marginal CNT benefits ($m = 5$, $B = 5,000$)

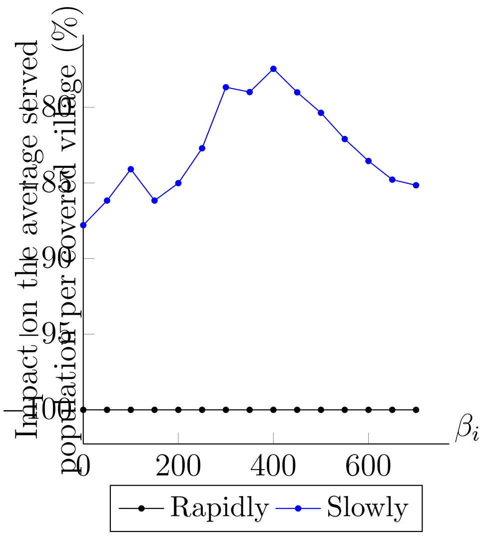


Figure 24: Average proportion of the population served at least **thrice** with rapidly and slowly decreasing marginal CNT benefits ($m = 5$, $B = 5,000$)

Second, we analyzed the logistics performance. Figure 25 reports the impact on the total cost (compared with constant marginal CNT benefits), whereas Figure 26 reports its proportion associated with location and routing costs. Compared with $\beta_i = 0$, the total cost decreases by 16% and 5% for rapidly decreasing and slowly decreasing marginal CNT benefits. More generally, rapidly decreasing and slowly decreasing marginal CNT benefits generally allow to decrease the total cost by an average of 10% and 7% due to a decrease in routing costs as the selected routes tend to visit fewer villages. Similarly to the other analyses, the largest portion of the total cost is attributed to the routing costs, i.e., more than 70% independently of the marginal CNT benefits. Figure 27 also reports the number of times each depot is selected for rapidly decreasing and slowly decreasing marginal CNT benefits over the 15 tested values of β_i. Independently on the marginal CNT benefits, there are either four or five open depots and a total of 50 routes with either 10 or 20 routes per depot. With rapidly decreasing marginal CNT benefits, three depots are used for more than 60% of the values of β_i, while four depots are used for more than 80% of the values of β_i with slowly decreasing marginal CNT benefits. Finally, the depot routing frequency does not seem to have a clear trend according to the marginal CNT benefits. This suggests that modifying the marginal CNT benefits allows to reduce the total cost while having robust solutions in terms of depot usage.

Our results show that using constant marginal CNT benefits allows for better coverage and continuity of care. In addition, while the depot usage is not sensitive to the choice of marginal CNT benefits, constant marginal CNT benefits have a higher total cost. We can thus conclude that using constant marginal CNT benefits, which is easier to model

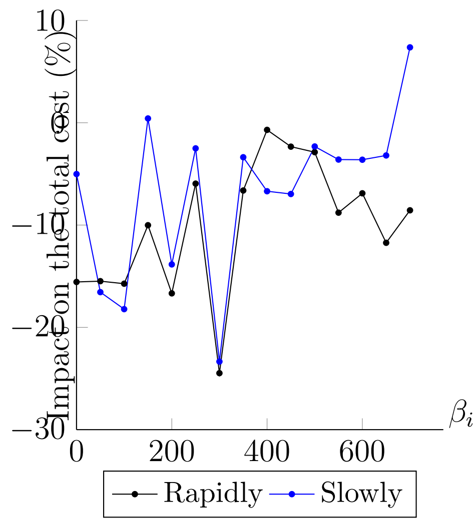


Figure 25: Impact on the total cost with rapidly and slowly decreasing marginal CNT benefits ($m = 5$, $B = 5,000$)

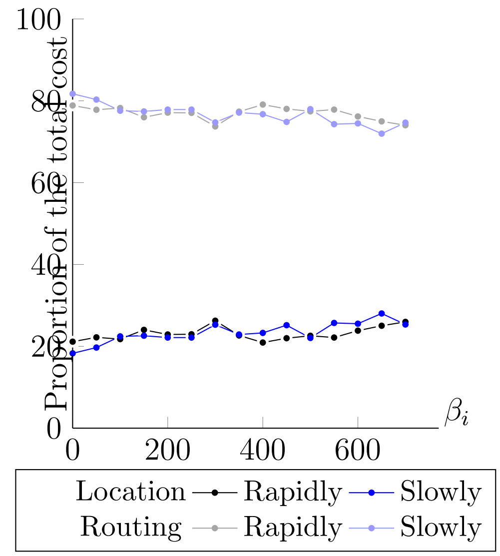
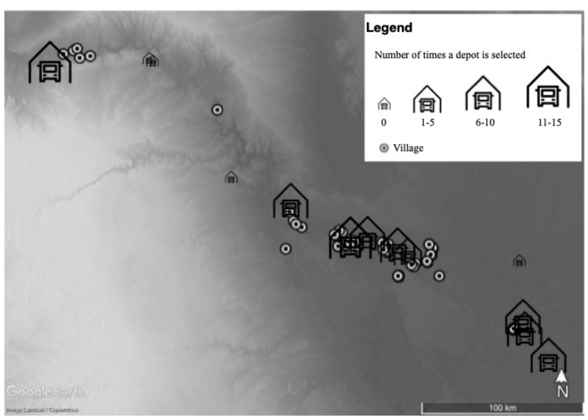
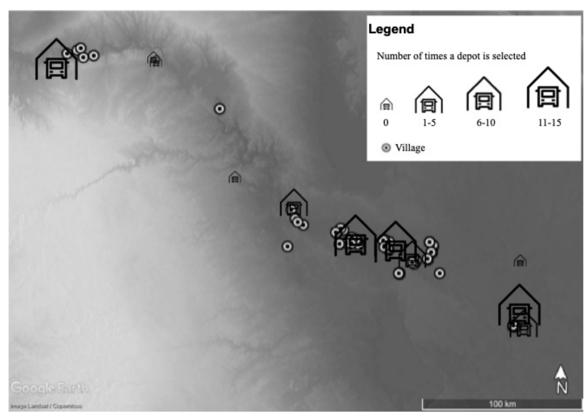


Figure 26: Proportion of the total cost associated with location and routing costs with rapidly and slowly decreasing marginal CNT benefits ($m = 5$, $B = 5,000$)



(a) Rapidly decreasing marginal CNT benefits



(b) Slowly decreasing marginal CNT benefits

Figure 27: Statistics on selected depots related to the marginal CNT benefits

and requires less parametrization, allows for robust and effective solutions in terms of healthcare performance and depot usage, which comes with an increase in total cost. Finally, our solution approach is not time sensitive with rapidly decreasing marginal CNT benefits, i.e., all solutions are found within 187 seconds, with an average of 88 seconds. With slowly decreasing marginal CNT 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.

5 Conclusions

In this paper, we introduced a new set-packing formulation for an MLRP for the tactical planning of mobile clinic deployments for humanitarian relief. Our model seeks to maximize the total healthcare benefit, considering both coverage and continuity of care. We also proposed indicators to measure the performance associated with the provided healthcare services and the logistics operations. The optimization model and the performance indicators are adapted to the context of mobile clinics aiming to outreach to vulnerable and underserved populations. These can also be used to systematically evaluate and identify the impact of strategic and tactical decisions on the deployments of mobile clinics.

Our solution approach was tested using real data from our partner (PUI) of a relief program implemented in Iraq, and our results have allowed us to derive managerial insights in that context. Using our collaborator's needs assessment scoring tool to derive the COV and CNT benefits, we tested fixed values of the COV benefit β_i from 0 to 700. We observed that as β_i is increased, the number of villages covered by the mobile clinics increases. However, CNT-v decreases as β_i increases. In addition, more than 70% of the total cost is associated with routing costs, there is no clear trend between the total cost and β_i. We show that a reasonable compromise between coverage and continuity is reached when $200 \leq \beta_i \leq 300$, while setting $\beta_i = 250$ might be a better choice in terms of the total cost. We conducted sensitivity analyses on the number of mobile clinics and the choice of marginal CNT benefit function. Our results show that increasing the available budget for this humanitarian program, and thus the number of mobile clinics, allows to cover more villages, whereas decreasing it reduce the coverage drastically. In addition, we show that the choice of marginal CNT benefit function does not seem to have a significant impact on the proposed solution, and therefore solutions obtained with constant marginal CNT benefits seem robust.

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. By collaborating with PUI we quantified the impact of their strategic decisions, i.e., the number of mobile clinics operated. On the other hand, the limited resources available only allow for a \$5,000 budget and five mobile clinics. With the proposed tool practitioners may explore the effect of a budget or resource increase without having to spend or invest ahead of time. For example, ending a route at a different depot implies that the medical personnel must be transported back to their vehicles or home locations. This provides evidence that practitioners may use to justify changes in policies and special requests to the respective board of directors or donors.

Our study fills a gap in the literature by formulating and solving a new MLRP. It allows to plan effective logistics operations in the case of mobile clinic deployment to increase outreach to underserved communities. It also serves as a tool 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 of care. This study will help our collaborators, as well as practitioners in the field, to justify decisions related to planning mobile clinic deployments.

Finally, multiple research avenues could be considered to expand the contributions of this paper. While our proposed model is deterministic, different sources of uncertainty (e.g., the travel time, the time required to treat a patient, and the number of patients per village) could be considered. However, quantifying, measuring, and modeling these sources of uncertainty, and including them in a representative stochastic model in the context of healthcare service offering in relief programs is challenging. Given that our proposed objective function computes the total healthcare benefit by considering the COV and CNT benefits, we believe that different multi-objective optimization methods (e.g., ϵ-contraint method and goal programming) could also be developed to further assess the trade-off between these COV and CNT benefits. Moreover, developing benchmark instances that represent the reality of managing mobile clinics would be a valuable contribution for the community conducting research in humanitarian logistics. These instances should reflect the specific characteristics of the underlying networks of different relief programs (e.g., security issues, population vulnerability, and limited resources).

Acknowledgments

We thank Première Urgence Internationale for their ongoing support and collaboration. Also we would like to thank Alain Vaillancourt for reaching out. While working on this project, T.G. Crainic was Adjunct Professor with the Department of Computer Science and Operations Research, Université de Montréal. Teodor Gabriel Crainic, Marie-Ève Rancourt, and Marilène Cherkesly were funded by the Canadian Natural Sciences and Engineering Research Council. Additionally, Marie-Ève Rancourt was funded by the Institute for Data Valorisation (IVADO). This research was also partially founded by the Centre de recherche sur l'intelligence[2] en gestion de systèmes complexes (CRI^2GS) of the School of Management Sciences, UQAM. This support is gratefully acknowledged. Thanks are due to the reviewers for their valuable comments.

References

Agyemang-Duah, W., Peprah, C., and Peprah, P. (2019). Barriers to formal healthcare utilisation among poor older people under the livelihood empowerment against poverty programme in the Atwima Nwabiagya district of Ghana. *BMC Public Health*, 19(1):1185–12.

Al-Attar, G. S., Bishai, D., and El-Gibaly, O. (2017). Cost-effectiveness analysis of family planning services offered by mobile clinics versus static clinics in Assiut, Egypt. *African Journal of Reproductive Health*, 21(1):30–38.

Albareda-Sambola, M., Fernández, E., and Nickel, S. (2012). Multiperiod location-routing with decoupled time scales. *European Journal of Operational Research*, 217(2):248–258.

Aljasir, B. and Alghamdi, M. (2010). Patient satisfaction with mobile clinic services in a remote rural area of Saudi Arabia. *EMHJ-Eastern Mediterranean Health Journal*, 16(10):1085–1090.

Archetti, C., Speranza, M., and Vigo, D. (2014). Chapter 10: Vehicle routing problems with profits. In *Vehicle Routing: Problems, Methods, and Applications, Second Edition*, pages 273–297. SIAM.

Arnette, A. N. and Zobel, C. W. (2019). A risk-based approach to improving disaster relief asset pre-positioning. *Production and Operations Management*, 28(2):457–478.

Arslan, O., Kumcu, G. Ç., Kara, B. Y., and Laporte, G. (2021). The location and location-routing problem for the refugee camp network design. *Transportation Research Part B: Methodological*, 143:201–220.

Balcik, B. (2017). Site selection and vehicle routing for post-disaster rapid needs assessment. *Transportation Research Part E: Logistics and Transportation Review*, 101:30–58.

Balcik, B. and Beamon, B. M. (2008). Facility location in humanitarian relief. *International Journal of Logistics*, 11(2):101–121.

Balcik, B., Beamon, B. M., and Smilowitz, K. (2008). Last mile distribution in humanitarian relief. *Journal of Intelligent Transportation Systems*, 12(2):51–63.

Balcik, B., Silvestri, S., Rancourt, M.-È., and Laporte, G. (2019). Collaborative prepositioning network design for regional disaster response. *Production and Operations Management*, 28(10):2431–2455.

Baumol, W. J. (1972). John R. Hicks' contribution to economics. *The Swedish Journal of Economics*, 74(4):503–527.

Bayliss, R. (1981). The medical check-up. *British Medical Journal (Clinical research ed.)*, 283(6292):631–634.

Bayraktar, O. B., Günneç, D., Salman, F. S., and Yücel, E. (2022). Relief aid provision to en route refugees: Multi-period mobile facility location with mobile demand. *European Journal of Operational Research*, 301(2):708–725.

Bechange, S., Roca, A., Schmidt, E., Gillani, M., Ahmed, L., Iqbal, R., Nazir, I., Ruddock, A., Bilal, M., Khan, I. K., Buttan, S., and Jolley, E. (2021). Diabetic retinopathy service delivery and integration into the health system in Pakistan—Findings from a multicentre qualitative study. *PLoS ONE*, 16(12):e0260936.

Beks, H., Ewing, G., Charles, J. A., Mitchell, F., Paradies, Y., Clark, R. A., and Versace, V. L. (2020). Mobile primary health care clinics for indigenous populations in Australia, Canada, New Zealand and the United States: A systematic scoping review. *International Journal for Equity in Health*, 19(1):1–21.

Belenguer, J.-M., Benavent, E., Prins, C., Prodhon, C., and Calvo, R. W. (2011). A branch-and-cut method for the capacitated location-routing problem. *Computers & Operations Research*, 38(6):931–941.

Berger, R. T., Coullard, C. R., and Daskin, M. S. (2007). Location-routing problems with distance constraints. *Transportation Science*, 41(1):29–43.

Besiou, M., Pedraza-Martinez, A. J., and Van Wassenhove, L. N. (2018). OR applied to humanitarian operations. *European Journal of Operational Research*, 269(2):397–405.

Blackwell, T. and Bosse, M. (2007). Use of an innovative design mobile hospital in the medical response to Hurricane Katrina. *Annals of Emergency Medicine*, 49(5):580–588.

Bowers, J., Cheyne, H., Mould, G., and Page, M. (2015). Continuity of care in community midwifery. *Health Care Management Science*, 18(2):195–204.

Breve, F., Batastini, L., LeQuang, J. A. K., and Marchando, G. (2022). Mobile narcotic treatment programs: On the road again? *Cureus*, 14(3).

Bruni, M. E., Conforti, D., Sicilia, N., and Trotta, S. (2006). A new organ transplantation location–allocation policy: A case study of Italy. *Health Care Management Science*, 9(2):125–142.

Burkart, C., Nolz, P. C., and Gutjahr, W. J. (2017). Modelling beneficiaries' choice in disaster relief logistics. *Annals of Operations Research*, 256(1):41–61.

Büsing, C., Comis, M., Schmidt, E., and Streicher, M. (2021). Robust strategic planning for mobile medical units with steerable and unsteerable demands. *European Journal of Operational Research*, 295(1):34–50.

Carello, G. and Lanzarone, E. (2014). A cardinality-constrained robust model for the assignment problem in home care services. *European Journal of Operational Research*, 236(2):748–762.

CBC News (2021). Eliminating barriers through mobile COVID-19 vaccine clinic. `https://www.cbc.ca/player/play/1882291267587`. [Accessed 30-September-2022].

Charles, A., Lauras, M., Van Wassenhove, L. N., and Dupont, L. (2016). Designing an efficient humanitarian supply network. *Journal of Operations Management*, 47:58–70.

Cherkesly, M., Rancourt, M.-È., and Smilowitz, K. R. (2019). Community healthcare network in underserved areas: Design, mathematical models, and analysis. *Production and Operations Management*, 28(7):1716–1734.

Chiappetta Jabbour, C. J., Sobreiro, V. A., Lopes de Sousa Jabbour, A. B., de Souza Campos, L. M., Mariano, E. B., and Renwick, D. W. S. (2019). An analysis of the literature on humanitarian logistics and supply chain management: Paving the way for future studies. *Annals of Operations Research*, 283(1):289–307.

Cinar, A., Salman, F. S., and Bozkaya, B. (2021). Prioritized single nurse routing and scheduling for home healthcare services. *European Journal of Operational Research*, 289(3):867–878.

Collinson, S. and Ward, R. (2010). A nurse-led response to unmet needs of homeless migrants in inner London. *British Journal of Nursing*, 19(1):36–41.

Contardo, C., Cordeau, J.-F., and Gendron, B. (2013). A computational comparison of flow formulations for the capacitated location-routing problem. *Discrete Optimization*, 10(4):263–295.

Contardo, C., Cordeau, J.-F., and Gendron, B. (2014). An exact algorithm based on cut-and-column generation for the capacitated location-routing problem. *INFORMS Journal on Computing*, 26(1):88–102.

Dantzig, G. B. and Ramser, J. H. (1959). The truck dispatching problem. *Management Science*, 6(1):80–91.

Dawkins, E., Michimi, A., Ellis-Griffith, G., Peterson, T., Carter, D., and English, G. (2013). Dental caries among children visiting a mobile dental clinic in South Central Kentucky: A pooled cross-sectional study. *BMC Oral Health*, 13(1):1–9.

de Roodenbeke, E., Lucas, S., Rouzaut, A., and Bana, F. (2011). *Outreach services as a strategy to increase access to health workers in remote and rural areas.* World Health Organization.

Dittmer, T. (2005). Diminishing marginal utility in economics textbooks. *Journal of Economic Education*, 36(4):391–399.

Doerner, K., Focke, A., and Gutjahr, W. (2007). Multicriteria tour planning for mobile healthcare facilities in a developing country. *European Journal of Operational Research*, 179(3):1078–1096.

Drexl, M. and Schneider, M. (2015). A survey of variants and extensions of the location-routing problem. *European Journal of Operational Research*, 241(2):283–308.

Du Mortier, S. and Coninx, R. (2007). Mobile health units in emergency operations: A methodological approach. *Humanitarian Practice Network, Network Papers*, 60:1–18.

Dufour, É., Laporte, G., Paquette, J., and Rancourt, M.-È. (2018). Logistics service network design for humanitarian response in East Africa. *Omega*, 74:1–14.

Ellen, J. M., Bonu, S., Arruda, J. S., Ward, M. A., and Vogel, R. (2003). Comparison of clients of a mobile health van and a traditional STD clinic. *Journal of Acquired Immune Deficiency Syndromes (1999)*, 32(4):388–393.

Feillet, D., Dejax, P., and Gendreau, M. (2005). Traveling salesman problems with profits. *Transportation Science*, 39(2):188–205.

Fikar, C. and Hirsch, P. (2017). Home health care routing and scheduling: A review. *Computers & Operations Research*, 77:86–95.

Fox-Rushby, J. A. and Foord, F. (1996). Costs, effects and cost-effectiveness analysis of a mobile maternal health care service in West Kiang, The Gambia. *Health Policy*, 35(2):123–143.

Gendreau, M., Laporte, G., and Semet, F. (1997). The covering tour problem. *Operations Research*, 45(4):568–576.

Gibson, J., Deng, X., Boe-Gibson, G., Rozelle, S., and Huang, J. (2011). Which households are most distant from health centers in rural China? Evidence from a GIS network analysis. *GeoJournal*, 76(3):245–255.

Grenouilleau, F., Lahrichi, N., and Rousseau, L.-M. (2020). New decomposition methods for home care scheduling with predefined visits. *Computers & Operations Research*, 115:104855.

Grenouilleau, F., Legrain, A., Lahrichi, N., and Rousseau, L.-M. (2019). A set partitioning heuristic for the home health care routing and scheduling problem. *European Journal of Operational Research*, 275(1):295–303.

Gunawan, A., Lau, H. C., and Vansteenwegen, P. (2016). Orienteering problem: A survey of recent variants, solution approaches and applications. *European Journal of Operational Research*, 255(2):315–332.

Guo, S., Biegel, D. E., Johnsen, J. A., and Dyches, H. (2001). Assessing the impact of community-based mobile crisis services on preventing hospitalization. *Psychiatric Services*, 52(2):223–228.

Gupta, S., Altay, N., and Luo, Z. (2019). Big data in humanitarian supply chain management: A review and further research directions. *Annals of Operations Research*, 283(1):1153–1173.

Hamedi, M., Haghani, A., and Yang, S. (2012). Reliable transportation of humanitarian supplies in disaster response: Model and heuristic. *Procedia-Social and Behavioral Sciences*, 54:1205–1219.

Hashemi, H., Rezvan, F., Yekta, A. A., Hashemi, M., Norouzirad, R., and Khabazkhoob, M. (2014). The prevalence of astigmatism and its determinants in a rural population of Iran: The "Nooravaran Salamat" mobile eye clinic experience. *Middle East African Journal of Ophthalmology*, 21(2):175–181.

Hauser, C. and Fremson, R. (2021). They haven't gone for a shot. So shots are coming to them. *The New York Times*. `https://www.nytimes.com/2021/05/20/us/mobile-vaccine-covid.html` [Accessed 30-September-2022].

Hodgson, M. J., Laporte, G., and Semet, F. (1998). A covering tour model for planning mobile health care facilities in Suhum District, Ghana. *Journal of Regional Science*, 38(4):621–638.

ICRC (2006). Mobile health units: A methodological approach. Technical report, International Committee of the Red Cross.

Irnich, S., Toth, P., and Vigo, D. (2014). Chapter 1: The family of vehicle routing problems. In *Vehicle Routing: Problems, Methods, and Applications, Second Edition*, pages 1–33. SIAM.

Jahre, M., Persson, G., Kovács, G., and Spens, K. M. (2007). Humanitarian logistics in disaster relief operations. *International Journal of Physical Distribution & Logistics Management*, 37(2):99–114.

Jamir, L., Nongkynrih, B., and Gupta, S. K. (2013). Mobile health clinics: Meeting health needs of the urban underserved. *Indian Journal of Community Medicine: Official Publication of Indian Association of Preventive & Social Medicine*, 38(3):132–134.

Kamali, M., Sivapalan, S., Kata, A., Kim, N., Shanmugalingam, N., Duku, E., Zwaigenbaum, L., and Georgiades, S. (2022). Program evaluation of a pilot mobile developmental outreach clinic for autism spectrum disorder in ontario. *BMC Health Services Research*, 22(1):1–14.

Konstantakopoulos, G. D., Gayialis, S. P., and Kechagias, E. P. (2022). Vehicle routing problem and related algorithms for logistics distribution: A literature review and classification. *Operational Research*, 22(3):2033–2062.

Kovacs, G., Moshtari, M., Kachali, H., and Polsa, P. (2019). Research methods in humanitarian logistics. *Journal of Humanitarian Logistics and Supply Chain Management*, 9(3):325–331.

Kunz, N., Van Wassenhove, L. N., Besiou, M., Hambye, C., and Kovacs, G. (2017). Relevance of humanitarian logistics research: Best practices and way forward. *International Journal of Operations & Production Management*, 37(11):1585–1599.

Laporte, G., Rancourt, M.-È., Rodríguez-Pereira, J., and Silvestri, S. (2022). Optimizing access to drinking water in remote areas. Application to Nepal. *Computers & Operations Research*, 140:105669.

Lee, D. and Ahn, J. (2019). Vehicle routing problem with vector profits with max-min criterion. *Engineering Optimization*, 51(2):352–367.

Lehoux, P., Daudelin, G., Poland, B., Andrews, G. J., and Holmes, D. (2007). Designing a better place for patients: Professional struggles surrounding satellite and mobile dialysis units. *Social Science and Medicine*, 65(7):1536–1548.

Lim, Z. H., Soo, Y. P., and Loo, J. H. Y. (2021). Clinical profiles of patients referred to an ear, nose and throat specialist clinic via community mobile hearing clinic in Singapore. *Proceedings of Singapore Healthcare*, 30(4):286–293.

Lopes, R. B., Ferreira, C., Santos, B. S., and Barreto, S. (2013). A taxonomical analysis, current methods and objectives on location-routing problems. *International Transactions in Operational Research*, 20(6):795–822.

Lukosch, H. and Comes, T. (2019). Gaming as a research method in humanitarian logistics. *Journal of Humanitarian Logistics and Supply Chain Management*, 9(3):352–370.

Maarsingh, O. R., Henry, Y., van de Ven, P. M., and Deeg, D. J. (2016). Continuity of care in primary care and association with survival in older people: A 17-year prospective cohort study. *British Journal of General Practice*, 66(649):e531–e539.

Maliki, F., Souier, M., Dahane, M., and Ben Abdelaziz, F. (2022). A multi-objective optimization model for a multi-period mobile facility location problem with environmental and disruption considerations. *Annals of Operations Research*, pages 1–26.

Martin, D., Wrigley, H., Barnett, S., and Roderick, P. (2002). Increasing the sophistication of access measurement in a rural healthcare study. *Health & Place*, 8(1):3–13.

Mas-Colell, A., Whinston, M. D., Green, J. R., et al. (1995). *Microeconomic theory*. Oxford University Press New York.

McGowan, C. R., Baxter, L., Deola, C., Gayford, M., Marston, C., Cummings, R., and Checchi, F. (2020). Mobile clinics in humanitarian emergencies: A systematic review. *Conflict and Health*, 14:4.

Milburn, A. B. and Spicer, J. (2013). Multi-objective home health nurse routing with remote monitoring devices. *International Journal of Planning and Scheduling*, 1(4):242–263.

Mor, A. and Speranza, M. G. (2022). Vehicle routing problems over time: A survey. *Annals of Operations Research*, pages 1–21.

Moreno, A., Alem, D., and Ferreira, D. (2016). Heuristic approaches for the multiperiod location-transportation problem with reuse of vehicles in emergency logistics. *Computers & Operations Research*, 69:79–96.

Mosquera, F., Smet, P., and Berghe, G. V. (2019). Flexible home care scheduling. *Omega*, 83:80–95.

Murphy, D. C., Klinghoffer, I., Fernandez-Wilson, J. B., and Rosenberg, L. (2000). Mobile health units: Design and implementation considerations. *AAOHN Journal*, 48(11):526–532.

Nagy, G. and Salhi, S. (2007). Location-routing: Issues, models and methods. *European Journal of Operational Research*, 177(2):649–672.

Naji-Azimi, Z., Renaud, J., Ruiz, A., and Salari, M. (2012). A covering tour approach to the location of satellite distribution centers to supply humanitarian aid. *European Journal of Operational Research*, 222(3):596–605.

Nickel, S., Schröder, M., and Steeg, J. (2012). Mid-term and short-term planning support for home health care services. *European Journal of Operational Research*, 219(3):574–587.

Oloruntoba, R. and Gray, R. (2006). Humanitarian aid: An agile supply chain? *Supply Chain Management: An International Journal*, 11(2):115–120.

Overstreet, R. E., Hall, D., Hanna, J. B., and Rainer, R. K. (2011). Research in humanitarian logistics. *Journal of Humanitarian Logistics and Supply Chain Management*, 1(2):114–131.

Parvin, H., Beygi, S., Helm, J. E., Larson, P. S., and Van Oyen, M. P. (2018). Distribution of medication considering information, transshipment, and clustering: Malaria in Malawi. *Production and Operations Management*, 27(4):774–797.

Peritogiannis, V., Papathanasiou, I. V., and Giotakos, O. (2022). Community psychiatry in rural Greece: The role of the mobile mental health units. *Psych*, 4(2):277–280.

Phillips, E., Stoltzfus, R. J., Michaud, L., Pierre, G. L. F., Vermeylen, F., and Pelletier, D. (2017). Do mobile clinics provide high-quality antenatal care? A comparison of care delivery, knowledge outcomes and perception of quality of care between fixed and mobile clinics in central Haiti. *BMC Pregnancy and Childbirth*, 17(1):1–11.

Prodhon, C. and Prins, C. (2014). A survey of recent research on location-routing problems. *European Journal of Operational Research*, 238(1):1–17.

PUI (2016). Mobile health teams in Iraq. https://www.premiere-urgence.org/en/mobile-health-teams-in-iraq/. [Accessed 30-September-2022].

Rancourt, M.-È., Cordeau, J.-F., Laporte, G., and Watkins, B. (2015). Tactical network planning for food aid distribution in Kenya. *Computers & Operations Research*, 56:68–83.

Rasmussen, M. S. and Larsen, J. (2011). *Optimisation-based solution methods for set partitioning models*. PhD thesis, Technical University of Denmark (DTU).

Robinson, V. and Segrott, J. (2002). *Understanding the decision-making of asylum seekers*. Home Office Research, Development and Statistics Directorate, London.

Rodríguez-Pereira, J., Balcik, B., Rancourt, M.-È., and Laporte, G. (2021). A cost-sharing mechanism for multi-country partnerships in disaster preparedness. *Production and Operations Management*, 30(12):4541–4565.

Salhi, S. and Rand, G. (1989). The effect of ignoring routes when locating depots. *European Journal of Operational Research*, 39(2):150–156.

Samakouri, M., Evagorou, O., and Frangouli-Sakellaropoulou, A. (2022). The contribution of mobile mental health units to community psychiatric care in Greece. *Psych*, 4(1):100–104.

Savaşer, S. (2017). *Periodic location routing problem: An application of mobile health services in rural area*. PhD thesis, Bilkent University.

Sphere Association (2018). *The Sphere handbook: Humanitarian charter and minimum standards in humanitarian response*. Fourth edition, Geneva, Switzerland.

Stauffer, J. M., Pedraza-Martinez, A. J., and Van Wassenhove, L. N. (2016). Temporary hubs for the global vehicle supply chain in humanitarian operations. *Production and Operations Management*, 25(2):192–209.

Tunalıoğlu, R., Koç, Ç., and Bektaş, T. (2016). A multiperiod location-routing problem arising in the collection of olive oil mill wastewater. *Journal of the Operational Research Society*, 67(7):1012–1024.

UNICEF (2018). UNICEF provides basic health care for children and families displaced from Afrin. https://www.unicef.org/syria/stories/unicef-provides-basic-health-care-children-and-families-displaced-afrin. [Accessed 30-September-2022].

United Nations (2018). Good health and well-being: Why it matters? https://www.un.org/sustainabledevelopment/wp-content/uploads/2018/09/Goal-3.pdf. [Accessed 30-September-2022].

United Nations (2019). Ensure healthy lives and promote well-being for all at all ages. https://unstats.un.org/sdgs/report/2019/goal-03/. [Accessed 30-September-2022].

United Nations (2022). About the sustainable development goals - United Nations sustainable development. https://www.un.org/sustainabledevelopment/sustainable-development-goals/. [Accessed 30-September-2022].

Vansteenwegen, P., Souffriau, W., and Van Oudheusden, D. (2011). The orienteering problem: A survey. *European Journal of Operational Research*, 209(1):1–10.

Veenstra, M., Roodbergen, K. J., Coelho, L. C., and Zhu, S. X. (2018). A simultaneous facility location and vehicle routing problem arising in health care logistics in the Netherlands. *European Journal of Operational Research*, 268(2):703–715.

Victoria, J. F., Afsar, H. M., and Prins, C. (2015). Vehicle routing problem with time-dependent demand in humanitarian logistics. In *2015 International Conference on Industrial Engineering and Systems Management (IESM)*, pages 686–694. IEEE.

Vidal, T., Crainic, T. G., Gendreau, M., and Prins, C. (2013). Heuristics for multi-attribute vehicle routing problems: A survey and synthesis. *European Journal of Operational Research*, 231(1):1–21.

Vidal, T., Laporte, G., and Matl, P. (2020). A concise guide to existing and emerging vehicle routing problem variants. *European Journal of Operational Research*, 286(2):401–416.

Vidal, T., Maculan, N., Ochi, L. S., and Vaz Penna, P. H. (2016). Large neighborhoods with implicit customer selection for vehicle routing problems with profits. *Transportation Science*, 50(2):720–734.

VonAchen, P., Smilowitz, K., Raghavan, M., and Feehan, R. (2016). Optimizing community healthcare coverage in remote Liberia. *Journal of Humanitarian Logistics and Supply Chain Management*, 6(3):352–371.

Whelan, C., Chambers, C., Chan, M., Thomas, S., Ramos, G., and Hwang, S. W. (2010). Why do homeless people use a mobile health unit in a country with universal health care? *Journal of Primary Care & Community Health*, 1(2):78–82.

Wirnitzer, J., Heckmann, I., Meyer, A., and Nickel, S. (2016). Patient-based nurse rostering in home care. *Operations Research for Health Care*, 8:91–102.

World Health Organization (2018). Health on wheels: mobile clinic brings vital care to displaced Yazidis in Iraq. https://medium.com/who/health-on-wheels-mobile-clinic-brings-vital-care-to-displaced-yazidis-in-iraq-a02f750df314. [Accessed 30-September-2022].

World Health Organization (2019). Delivering health in some of the worlds' worst crises through mobile clinics and medical teams. https://www.who.int/news-room/feature-stories/detail/delivering-health-in-some-of-the-worlds-worst-crises-through-mobile-clinics-and-medical-teams. [Accessed 30-September-2022].

Wray, N. P., Weiss, T. W., Menke, T. J., Gregor, P. J., et al. (1999). Evaluation of the VA mobile clinics demonstration project. *Journal of Healthcare Management*, 44(2):133–147.

Yi, W. and Özdamar, L. (2007). A dynamic logistics coordination model for evacuation and support in disaster response activities. *European Journal of Operational Research*, 179(3):1177–1193.

A Detailed computational results

Table 7 contains the detailed computational results when fixing $m = 5$ and $B = 5,000$ with equal division of the population in routes, and for the three CNT benefit functions (constant marginal CNT benefits, rapidly decreasing CNT benefits and slowly decreasing CNT benefits). Then, for each CNT 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. In addition, for a given CNT benefit function, because the value of $\beta_i^v, \forall i \in \mathcal{N}^c, v \in \mathcal{V}$ (i.e., the CNT benefit) remains constant, the increase in the objective function is expected. Finally, comparing the objective function between the different CNT 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 7: Detailed computational results $m = 5$, $B = 5,000$, and equal division of population in routes

	Constant		Rapidly decreasing		Slowly decreasing	
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 8 contains the detailed computational results when fixing $m = 5$ and $B = 5,000$ with constant marginal CNT benefits for *population proportion*, *score proportion*, *vulnerability proportion*, and *accessibility proportion*. Note that the results for *equal proportion* have been presented in Table 7. The first column contains the COV benefit per location i (β_i). Then, for each way to divide the number of patients in a route, we present: the optimal solution value (z^*), and the total computational time in seconds (*Sec.*).

Table 9 contains the detailed computational results when fixing $m = 5$ and $B = 5,000$

Table 8: Detailed computational results $m = 5$, $B = 5,000$, and constant marginal CNT 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

with constant marginal CNT benefits for *equal proportion* when allowing all regular routes (including regular routes that start and end at different depots). The table is organized as follows: we report the COV benefit per location i (β_i), the optimal solution value (z^*), and the total computational time in seconds (*Sec.*).

Table 9: Detailed computational results $m = 5$, $B = 5,000$, constant marginal CNT benefits, equal proportion and regular routes that start and end at different depots

β_i	z^*	Sec.
0	113,750	281
50	114,506	268
100	115,340	273
150	116,395	282
200	117,707	303
250	119,150	299
300	120,620	288
350	122,461	301
400	124,566	437
450	126,759	372
500	128,961	397
550	131,161	519
600	133,361	431
650	135,561	478
700	137,759	364

B Impact of the number of individuals visited at each village in a route

In its current program, our partner divides the total number of patients that are examined or treated in a route (50) equally between covered villages in every route (see Section 4.3), which implies that all villages are of equal importance. In practice, villages are heterogeneous according to their population, their need for healthcare, their vulnerability score, and their accessibility to healthcare. Therefore, these factors should be considered to evaluate the effectiveness of the current policy. In the following, we aim to examine if alternative ways of dividing the number of visits impact the solutions and their performance.

Four alternatives to determine the number of individuals served at each village in a route have been considered, i.e., dividing the capacity of the number of patients that can be served in a route:

1. Poportional to the population of the villages, denoted as *population proportion* (*Pop.*), by using p_i the population seeking healthcare at village i;
2. Proportional to the health score of the villages, denoted as *score proportion* (*Score*), by using s_i the health score of village i;
3. Proportional to the vulnerability score (e.g., pregnant women, children, and elderly) of the villages, denoted as *vulnerability proportion* (*Vul.*), by using s_i^1 the vulnerability score of village i determined by PUI during the healthcare needs assessment;
4. Proportional to the accessibility to healthcare of the villages, denoted as *accessibility proportion* (*Acc.*), by using s_i^2 the accessibility score of village i computed by PUI during the healthcare needs assessment.

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 patients served at village i, G_{i_1,r_1}, will vary according to the way we compute this number. With *population proportion*, the number of patients served is

$$G_{i_1,r_1} = \left\lfloor Q\frac{p_{i_1}}{p_{i_1}+p_{j_1}} \right\rfloor \text{ and } G_{j_1,r_1} = \left\lfloor Q\frac{p_{j_1}}{p_{i_1}+p_{j_1}} \right\rfloor. \tag{18}$$

With (i) *score proportion*, (ii) *vulnerability proportion*, and (iii) *accessibility proportion*, Equation (18) would be modified by replacing p_{i_1} and p_{j_1} by (i) s_{i_1} and s_{j_1}, (ii) $s_{i_1}^1$ and $s_{j_1}^1$, and (iii) $s_{i_1}^2$ and $s_{j_1}^2$.

First, we analyzed the impact on the healthcare performance, i.e., the impact on the number of covered villages as well as CNT-v (Figures 28–31). When $\beta_i = 0$, 15

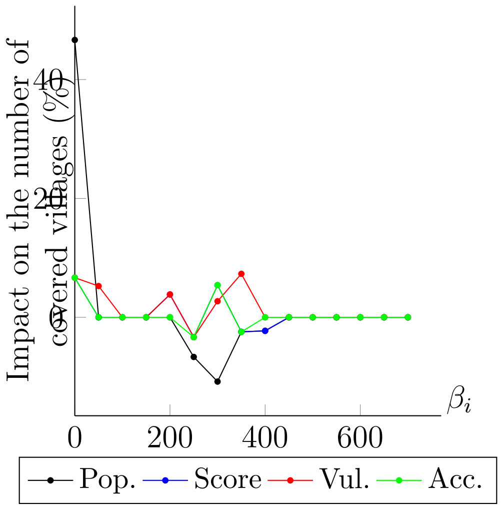


Figure 28: Impact on the number of covered villages when considering the number of visits at each village ($m = 5$, $B = 5,000$)

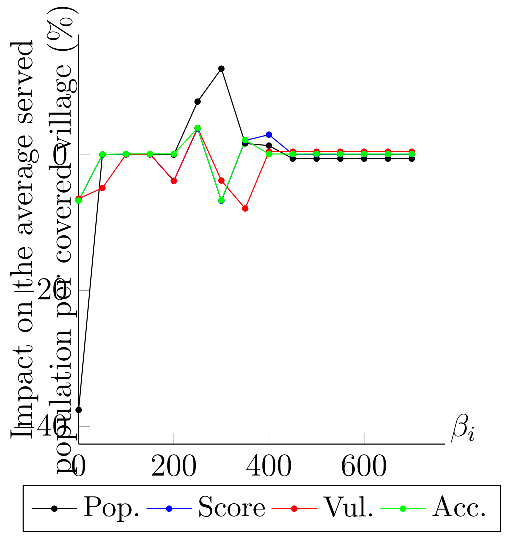


Figure 29: Average proportion of the population served at least **once** when considering the number of visits at each village ($m = 5$, $B = 5,000$)

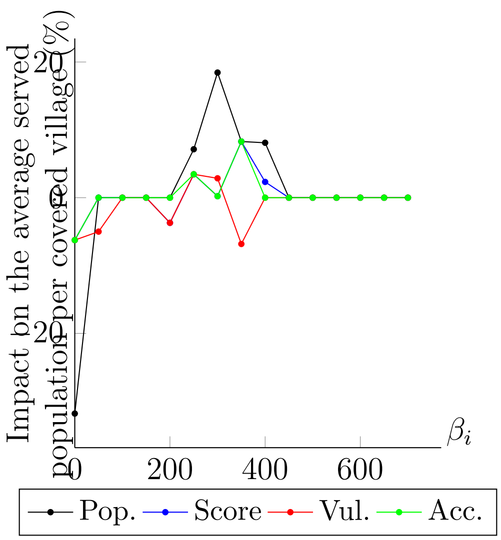


Figure 30: Average proportion of the population served at least **twice** when considering the number of visits at each village ($m = 5$, $B = 5,000$)

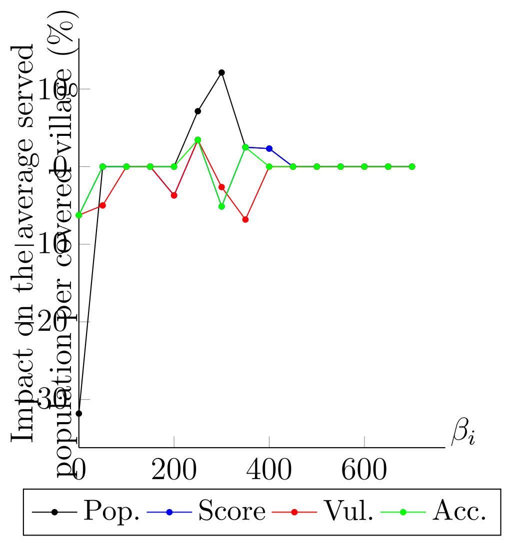


Figure 31: Average proportion of the population served at least **thrice** when considering the number of visits at each village ($m = 5$, $B = 5,000$)

to 22 villages are covered depending on how the number of patients served at each village is determined, and the population served at least once decreases compared to the *equal proportion* capacity-allocation policy. Compared with the *base case*, using the *population proportion* capacity-allocation policy allows to cover the most villages (i.e.,

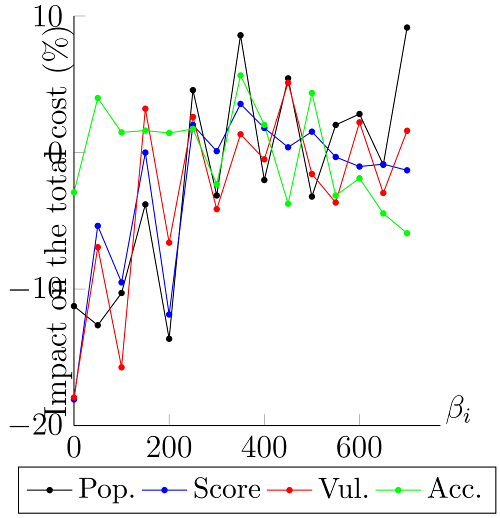


Figure 32: Impact on the total cost when considering the number of visits at each village ($m = 5$, $B = 5,000$)

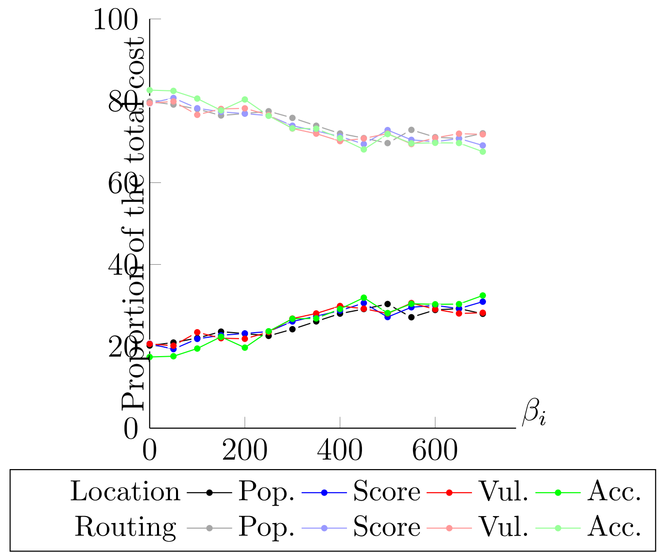
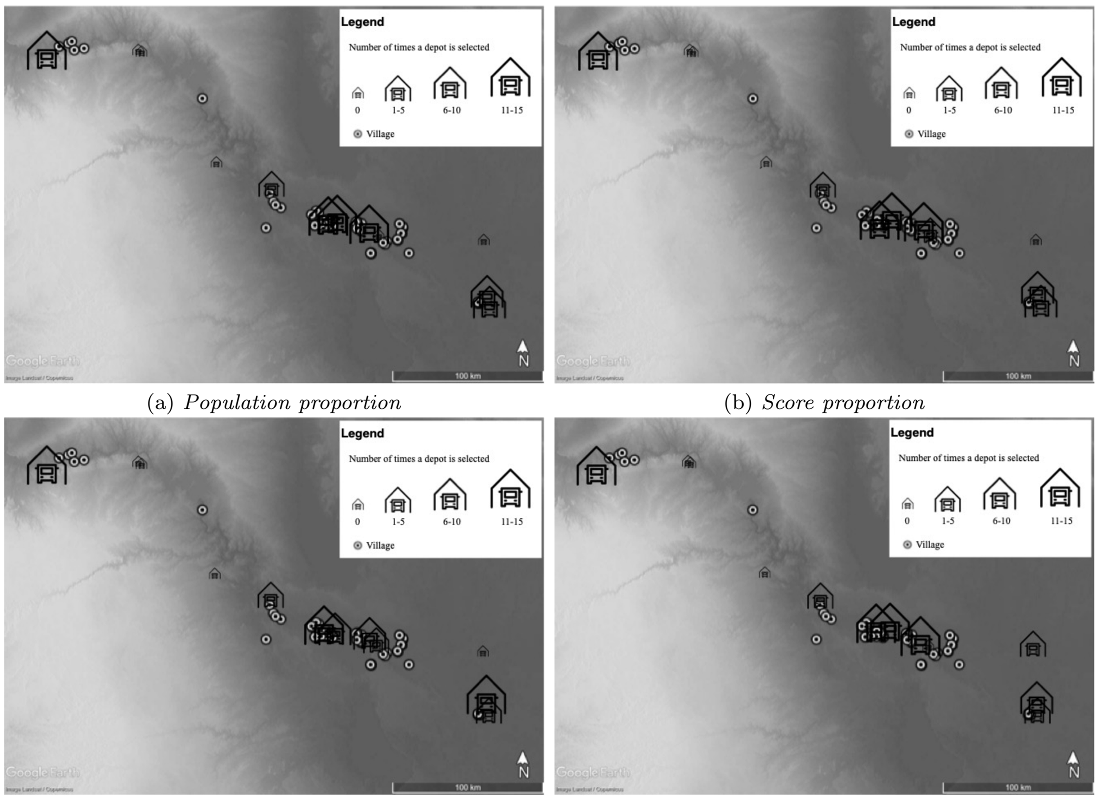


Figure 33: Proportion of the total cost associated with location and routing costs when considering the number of visits at each village ($m = 5$, $B = 5,000$)

7 additional villages for a total of 22 villages), while the three other capacity-allocation policie (*score proportion*, *vulnerability proportion*, and *accessibility proportion*) allow to cover one additional village. Given that more villages are covered, CNT-1, CNT-2, and CNT-3 decrease. When using the *score proportion*, *vulnerability proportion*, and *accessibility proportion* capacity-allocation policies, there is a variation of at least –6%, while this variation is of at least –32% with *population proportion*. When $\beta_i \leq 50$, the number of covered villages remains relatively similar independently on the number of individuals visited at each village in a route. In addition, CNT-1, CNT-2, and CNT-3 remain relatively constant, while we can notice a slight increase of CNT-1 when $250 \leq \beta_i \leq 400$ due to the decrease in the number of covered villages. Therefore, the number of patients served (examined or treated) per village does not seem to have an impact on coverage and continuity of care.

Second, we analyzed the logistics performance. Figure 32 reports the impact on the total cost (compared with *equal proportion*), while Figure 33 reports the proportion associated with location and routing costs. When $\beta_i = 0$, the total cost decreases by at least 3% with the *accessibility proportion* capacity-allocation policy and up to 18% with the *score proportion* and *vulnerability proportion* capacity-allocation policies. More generally, the total cost decreases by an average between 2% and 3% according to how the number of patients served at each village in a route is computed. Similarly to the other analyses, the largest proportion of the total cost is associated with the routing costs, but as the value of β_i increases this proportion decreases which is due to the increased number of covered villages. In terms of depot usage, Figure 34 reports the number of times each depot is selected. For all the cases, there are either four or five open depots with either 10 or 20 routes per depot for a total of 50 routes. The four same depots are opened for more than 60% of the cases which suggests that the depot selection frequency is not very sensitive to how the number of patients served at each village in a route is computed. There is also no clear trend in terms of depot routing frequency.



(a) *Population proportion* (b) *Score proportion*

(c) *Vulnerability proportion* (d) *Accessibility proportion*

Figure 34: Statistics on selected depots related to the number of individuals visited at each village

Considering this analysis, we can conclude that when modifying how the number of patients served in the villages covered in a route is computed, the performance indicators as well as the solutions remain similar. The biggest change concerns an average reduction of the total cost between 2% and 3% overall all values of β_i. In addition, the total computational time is not affected; all solutions are found within 260 seconds with an average of 100 seconds. This implies that the current policy of dividing equally the number of patients served at each village in a route, which is the simplest, performs well both in terms of healthcare and logistics performances in this case. Note that independently of the number of visits at each village in a route and the CNT benefit function, larger villages are covered when β_i increases. However, the average score of the covered villages remains relatively constant when β_i increases (see Figures 35–38). Thus, although small villages might be favored when less weight is given to coverage as opposed to continuity of care, the most vulnerable villages are covered, which is important as a priority should be given to the highest needs in humanitarian relief.

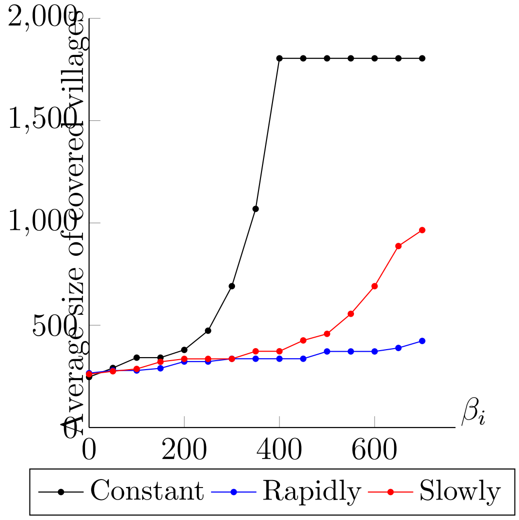


Figure 35: Average size of covered villages according to the marginal CNT benefits ($m = 5$, $B = 5,000$)

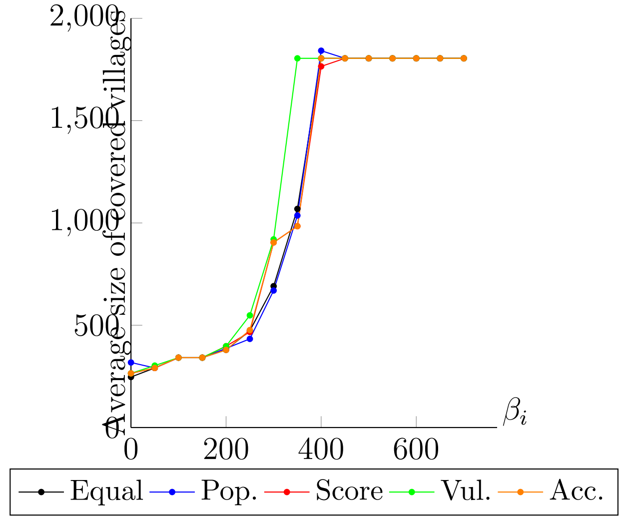


Figure 36: Average size of covered villages when considering the number of visits at each village ($m = 5$, $B = 5,000$)

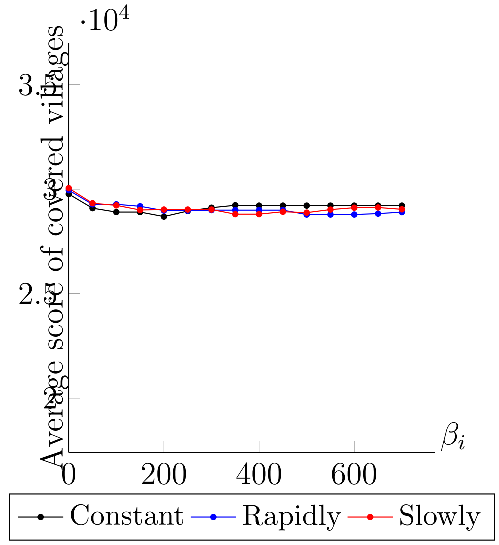


Figure 37: Average score of covered villages according to the marginal CNT benefits ($m = 5$, $B = 5,000$)

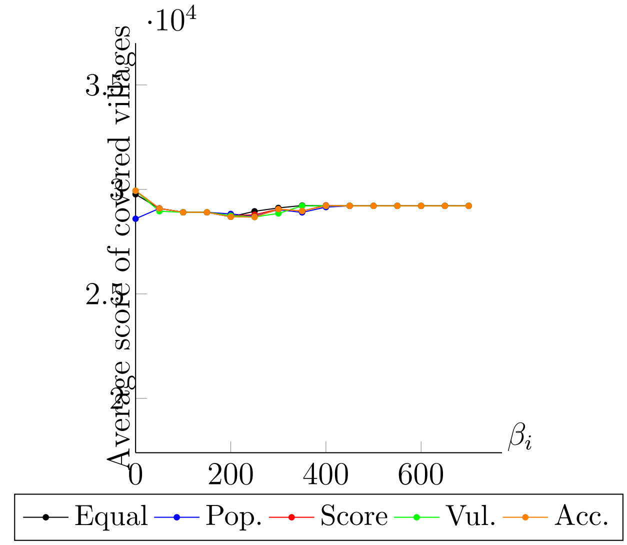


Figure 38: Average score of covered villages when considering the number of visits at each village ($m = 5$, $B = 5,000$)

C Impact of allowing all regular routes

As explained in Section 4.3, our partner only allows a subset of regular routes, i.e., routes that start and end at the same depot. In practice, there are cases where it could be possible to allow routes that start and end at different depots while covering a subset of villages. These types of routes may allow for better coverage or continuity of care. Therefore, in this section, we determine the impact of allowing routes that start and end at different depots. When considering these routes, the set of generated routes increases from 2,711 in the *base case* to 17,652, which increases the computational time while all solutions are solved within less than 600 seconds.

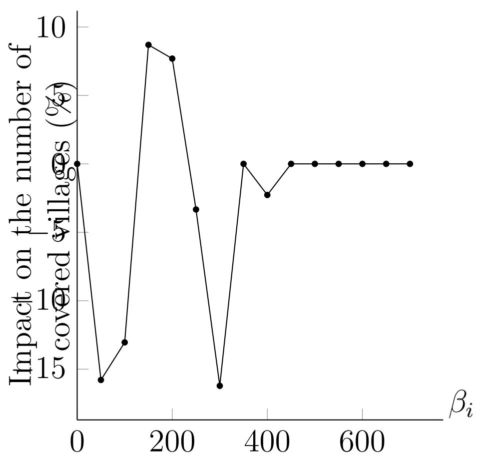


Figure 39: Impact on the number of covered villages when considering regular routes starting and ending at different depots ($m = 5$, $B = 5,000$)

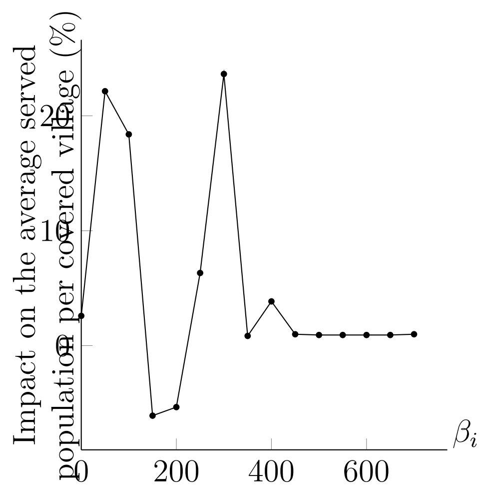


Figure 40: Average proportion of the population served at least **once** when considering regular routes starting and ending at different depots ($m = 5$, $B = 5,000$)

First, we compared the number of covered villages as well as the average proportion of the population served at least once, twice, and thrice, see Figures 39–42. Compared with the *base case* ($\beta_i = 0$), our results show that the number of covered villages does not vary, but we note a variation of 3%, 16%, and 0% of CNT-1, CNT-2, and CNT-3. More generally, we observe that considering regular routes that begin and end at different depots yields a decrease in the number of covered villages. In particular, when $\beta_i = \{50, 100, 250, 300, 400\}$ the number of covered villages decreases between 2% and 16%, which results in an increase of CNT-1 (between 4% and 24%), CNT-2 (between 20% and 47%), and CNT-3 (between 3% and 20%). We can also notice that when the number of covered villages remains the same ($\beta_i = \{0, 350, 450, 500, 550, 600, 650, 700\}$), there is an increase on the average values of CNT-1 (between 1% and 3%) and CNT-2 (between 16% and 23%), while there is no impact on CNT-3. Finally, when $\beta_i = \{150, 200\}$, we

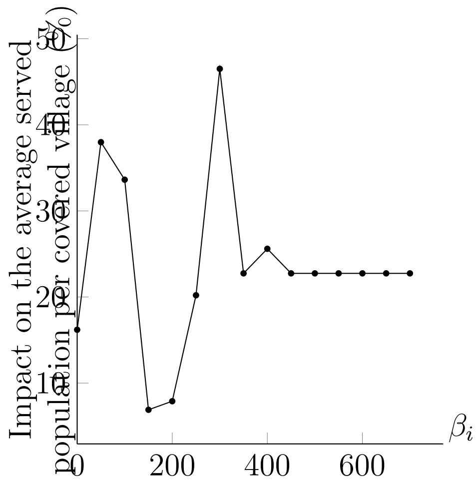


Figure 41: Average proportion of the population served at least **twice** when considering regular routes starting and ending at different depots ($m = 5$, $B = 5,000$)

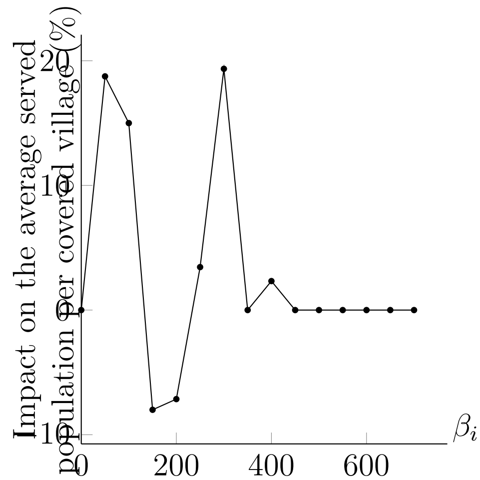


Figure 42: Average proportion of the population served at least **thrice** when considering regular routes starting and ending at different depots ($m = 5$, $B = 5,000$)

note an average increase of 8% on the number of covered villages, which results in an average decrease of 6%, 7%, and 8% on CNT-1, CNT-2, and CNT-3.

Second, we compared the logistics performance both in terms of the total cost, as well as depot usage. Figures 43 and 44 report the impact on the total cost as well as the proportion of the total cost associated with location and routing costs. Compared with the *base case*, we can note an increase of 13% due to an increase in the number of open depots (i.e., eight depots are opened instead of five) as well as an increase in the routing costs as the selected routes tend to be longer (i.e., 60% of the routes start and end at different depots). More generally, the routing costs increase by an average of 14% for the same reasons. Figure 45 shows the depot selection frequency. Eight depots are opened for most values of β_i, except for $\beta_i = 100$ where seven depots are opened, and from these depots, 60% of the routes start and end at different depots. Although the depot usage is not sensitive to the increase in β_i, it is sensitive when comparing routes that start and end at the same depot.

Our analysis shows that allowing routes that start and end at different depots, rather than routes that start and end at the same depot, usually increases continuity of care without any impact on coverage ($\beta_i = \{0, 350, 450, 500, 550, 600, 650, 700\}$), or with a decrease of less than 16% on the number of covered villages ($\beta_i = \{50, 100, 250, 300, 400\}$). This comes with an average increase of the total cost of 14% due to the increased number of depots as well as the increased routing costs (i.e., 60% of the routes start and end at different depots). Therefore, while the improvements in healthcare performance are

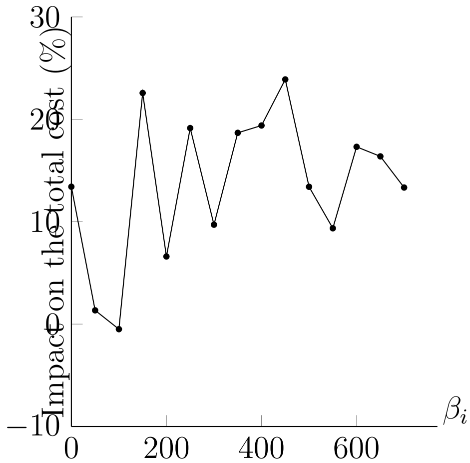


Figure 43: Impact on the total cost when considering regular routes starting and ending at different depots ($m = 5$, $B = 5,000$)

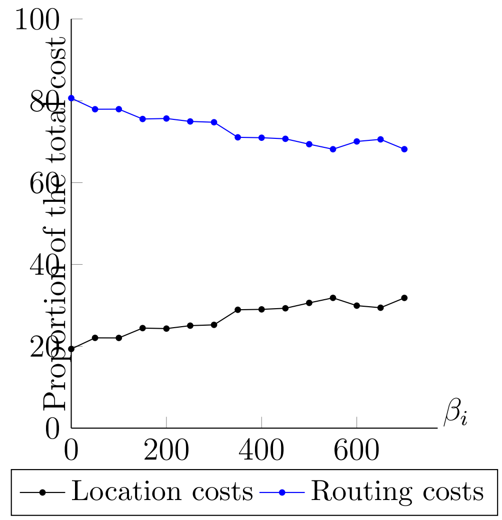


Figure 44: Proportion of the total cost associated with location and routing costs when considering regular routes starting and ending at different depots ($m = 5$, $B = 5,000$)

limited, this decreases the logistics performance.

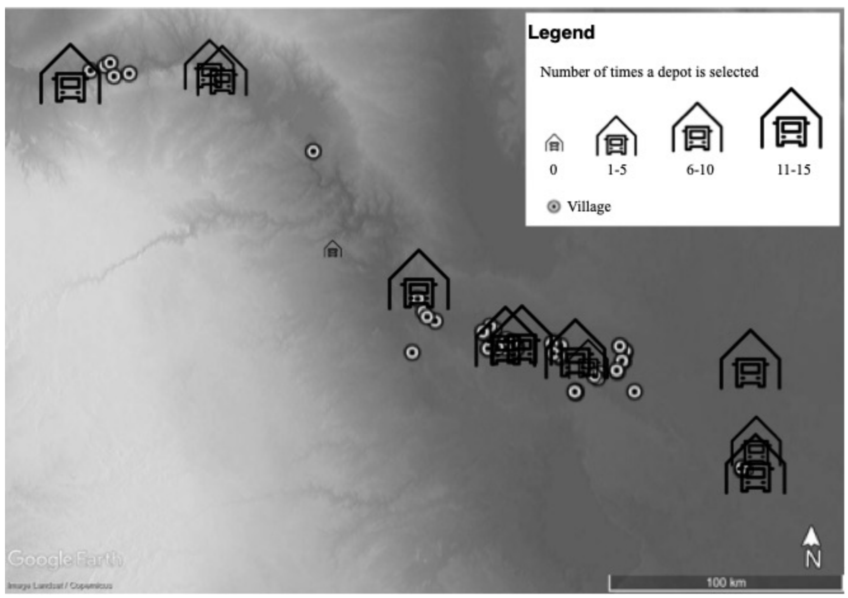


Figure 45: Statistics on selected depots related allowing all regular routes