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Planning of Mobile Clinic Operations

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Résumé

Cette thèse vise à contribuer à la littérature sur la gestion des opérations des cliniques mobiles. Les cliniques mobiles sont souvent mises en place dans un contexte humanitaire. Elles permettent aux professionnels de la santé d'offrir leurs services dans des zones mal desservies (c'est-à-dire des zones qui ont un accès limité aux établissements de santé). Par exemple, les cliniques mobiles sont utilisées après les guerres pour servir les populations qui rentrent chez elles. De même, les cliniques mobiles sont utilisées pour fournir des services de planification familiale dans les pays en développement. Cette thèse se concentre sur la planification tactique des opérations des cliniques mobiles. En effet, il est courant que les gestionnaires des cliniques mobiles soient confrontés à des défis dans la phase tactique du processus de planification après que les organisations à but non lucratif aient reçu des directives des donateurs et des conseils d'administration concernant le plan stratégique. Il n'existe pas d'outil ou de guide complet permettant de répondre aux défis de la planification tactique. La méthodologie proposée dans cette thèse est fondée sur les principes de la recherche opérationnelle (collecte de données et définition du problème, modélisation mathématique, développement d'un algorithme de résolution et validation des résultats). En étudiant les défis rencontrés par les gestionnaires des cliniques mobiles, et en les représentant à l'aide de modèle mathématiques, cette thèse cherche à fournir des outils de planification tactique auxdits gestionnaires, mais aussi aux chercheurs du domaine. Nous commençons par étudier la littérature pour identifier les lacunes actuelles et souligner l'importance et la complexité des déploiements de cliniques mobiles. Nous développons ensuite deux outils de planification tactique pour aider

les gestionnaires et utilisateurs des cliniques mobiles. Le premier outil de planification s'attaque au choix des sites que les cliniques mobiles vont visiter, aux itinéraires suivis par les cliniques mobiles, et à la fréquence des visites des cliniques mobiles pendant la phase tactique. Le second outil intervient après l'identification des emplacements des cliniques : il s'occupe de la population desservie et des tournées des cliniques mobiles dans un contexte d'incertitude. L'utilisation de l'outil de planification permet d'obtenir des informations sur les politiques d'ajustement du plan tactique proposé. La thèse est divisée en trois chapitres. Les chapitres un et deux ont été développés dans le cadre d'une collaboration avec l'organisation humanitaire internationale Première Urgence Internationale (PUI), qui déploie des cliniques mobiles dans le monde entier.

Chapitre 1. Le premier chapitre passe en revue la littérature relative aux cliniques mobiles. En combinant une revue intégrative de la littérature et une étude instrumentale de cas, il positionne l'utilisation des déploiements de cliniques mobiles pour l'aide humanitaire dans les urgences complexes ou les zones de conflit. L'analyse documentaire intégrative combine deux analyses documentaires ciblées, l'une sur les cliniques mobiles et l'autre sur les conflits, en raison du manque de documentation sur les cliniques mobiles dans les zones de conflit. L'étude de cas instrumentale documente le déploiement de cliniques mobiles pendant la guerre en Irak afin d'illustrer et de souligner les particularités en zone de conflit. Les lacunes de la littérature ainsi que les futures questions de recherche sont soulignées pour servir de guide aux chercheurs et aux gestionnaires des cliniques mobiles. Cette revue de la littérature sert également à justifier la pertinence des chapitres deux et trois.

Chapitre 2. Le deuxième chapitre présente le problème de planification tactique déterministe pour le déploiement de cliniques mobiles. Nous avons modélisé la planification du déploiement de cliniques mobiles comme un problème de localisation et de tournées de véhicules multi-périodes (MLRP) afin de considérer la temporalité des déploiements de cliniques mobiles pour l'aide humanitaire en matière de santé. Pour résoudre le MLRP, une formulation de type *set-packing* qui repose sur la génération de routes a été mise en œuvre. L'optimisation du modèle proposé permet de sélectionner les dépôts et les routes de véhicules qui seront exécutées à chaque période de l'horizon de planification, c'est-à-dire les plans tactiques où l'aide humanitaire est quantifiée comme l'avantage de couvrir des emplacements et de servir la population. Les résultats sont présentés pour une application du déploiementde cliniques mobiles en Irak géré par PUI, y compris des analyses de sensibilité sur la modélisation des avantages de la couverture et de la continuité des soins, et les impacts de certaines décisions organisationnelles stratégiques et tactiques comme, par exemple, le nombre de cliniques mobiles disponibles. En outre, nos émettons des recommandation de gestion découlant des résultats obtenus. Nous présentons un problème de localisation et tournées de véhicules multi-périodes (MLRP) présentant des avantages pour la planification tactique du déploiement de cliniques mobiles. La formulation proposée de *set-packing* vise à sélectionner les communautés à desservir et à concevoir les routes à effectuer tout au long de l'horizon de planification de manière à maximiser l'accessibilité aux soins de santé, mesurés au moyen des fonctions de couverture et de continuité des soins. Les résultats sont présentés pour une application basée sur les opérations de PUI en Irak, y compris des analyses de sensibilité sur les paramètres utilisés pour modéliser les avantages en matière de santé.

Chapitre 3. Le troisième chapitre présente une méthodologie de planification tactique qui tient compte de l'incertitude qui se présente dans le contexte des cliniques mobiles. Les gestionnaires des cliniques s'efforcent de déployer des cliniques qui peuvent accéder aux populations ayant les plus grands besoins. Cependant, lors de la planification d'opérations humanitaires, des sources d'incertitude apparaissent quant à la durée du voyage, à l'utilisation des routes et à l'accès aux aux villages. Cette étude modélise le déploiement de cliniques mobiles comme un problème stochastique de collecte de bénéfices en deux étapes qui maximise le bénéfice offert (donner des soins) et minimise les coûts attendus, tout en considérant plusieurs sources d'incertitude affectant le temps de déplacement, l'utilisabilité des routes et l'accessibilité aux villages. L'impact de quatre politiques d'ajustements du plan aux nouvelles informations concernant l'état du système (i.e., recours) sur les plans de déploiement des cliniques mobiles est également étudié. Ces quatre politiques sont le recours simple, le sélection des villages en premier et les

tournées en deuxième, le recours par période, et le recours complet. Le recours simple implique de ne pas effectuer les itinéraires qui violent les contraintes, la sélection des villages en premier et les tournées en deuxième implique de ne pas sélectionner les itinéraires jusqu'à ce que l'incertitude soit révélée, le recours par période signifie qu'un recours est effectué tout en assurant que les villages soient visités à la période préétablie ou pas du tout, et, enfin, le recours complet permet une restructuration complète des itinéraires. La performance des politiques d'ajustements des plans est évaluée pour trois niveaux de sévérité des sources d'incertitude : modéré, moyen et sévère. Les résultats et les perspectives de gestion sont présentés pour différentes instances du monde réel, qui représentent différentes caractéristiques du réseau (c.-à-d., niveau de densité et structure du réseau).

Mots-clés

Cliniques mobiles, secours en cas de catastrophe, logistique humanitaire, équipes d'unités mobiles, routes multi-périodes, programmation stochastique, incertitude du temps de déplacement, accessibilité des lieux, utilité des routes, planification tactique des opérations.

Abstract

This thesis aims to contribute to the literature of mobile clinics operations management. Mobile clinics are often implemented in a humanitarian context. They allow healthcare practitioners to offer their services in underserved areas (i.e., areas that have limited access to healthcare facilities). For example, mobile clinics are used after wars to serve populations returning to their homes. Also, mobile clinics are used to provide family planning services in developing nations. This thesis focuses on the tactical planning of mobile clinics operations. As it is common for practitioners to face challenges in the tactical planning phase after non-for-profit organizations have received directions from donors and boards of directors regarding the strategical plan. However, there is no comprehensive tool or guide addressing tactical planning challenges. The methodology developed is based on the principles of operations research (data collection and problem definition, mathematical modeling, development of solution algorithm, and validation of results). By studying the challenges and capturing them with mathematical models we aim to provide tactical planning tools and managerial insights for practitioners and researchers. We start by surveying the literature to identify gaps and highlight the importance and complexity of mobile clinic deployments. Then we develop tactical planning tools to aid practitioners. The first planning tool tackles location selection, vehicle routing, and visit-frequency planning during the tactical phase. The second tool address the tactical plan after the identification of departure locations for the clinic, it concentrates on the population served and the mobile clinic routes in a context of uncertainty. This planning tool is used to derive insights on the proposed tactical plan adjustment policies. The thesis is divided into three

chapters. Chapter one and two were developed as part of a collaboration with the international humanitarian organization Première Urgence Internationale (PUI), which deploys mobile clinics around the world .

Chapter 1. The first chapter surveys the literature pertinent to mobile clinics. By combining an integrative literature review and an instrumental case study, it positions the use of mobile clinic deployments for humanitarian relief in complex emergencies or conflict zones. The integrative literature review combines two targeted literature reviews, one on mobile clinics and another on conflicts due to the dearth of literature on mobile clinics in conflict zones. The instrumental case study documents a mobile clinic deployment during the Iraq War to illustrate and highlight the peculiarities of deploying mobile clinics in conflict zones. The gaps in the literature as well as future research questions are highlighted to serve as a guide for researchers and practitioners. This literature review also serves to justify the relevance of chapters two and three.

Chapter 2. The second chapter presents the tactical planning problem for the deployment of mobile clinics. We present a multiperiod location-routing problem (MLRP) with benefits for the tactical planning of mobile clinic deployment. The proposed set-packing formulation aims to select communities to be served and design routes to be performed throughout the planning horizon such that health benefits, measured by means of coverage and continuity of care functions, are maximized. 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.

Chapter 3. The third chapter presents a tactical plan that explicitly considers the uncertainty that arises in the context of mobile clinics. Practitioners strive to deploy clinics that can access populations with the highest needs. However, when planning humanitarian operations, uncertainty in the travel times, usability of roads, and access to population points. This study models mobile clinic deployment as a two-stage stochastic benefit collection problem (SPBC) that maximizes the benefit offered and minimizes the expected

costs, while considering several sources of uncertainty affecting the travel time, usability of roads, and access to population points. The impact of four policies for adjusting the plan to new information about system status (i.e., recources) on mobile clinic deployment plans is also studied. Where the simple recourse entails not performing routes that violate constraints, the select-then-route policy implies not selecting the routes until the uncertainty is revealed, the re-route per time period policy means that a rerouting is performed while ensuring the population points are visited at the pre-established period or not at all, and, finally, the full network recourse allows for a complete restructure of the routes. The recourse policies' performance is evaluated on three different severity levels of uncertainty: moderate, medium, and severe. Results and managerial insights are presented for different real-world instances, that represent different network structures (i.e., sparse/rural and grid/city settings).

Keywords

Mobile Clinics, Disaster Relief, Humanitarian Logistics, Mobile Unit Teams, Multiperiod Location Routing, Stochastic Programming, Travel Time Uncertainty, Accessibility, Usability of Roads, Tactical Planning

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List of acronyms

OR/MS Operations Research and Management Science

MLRP Multiperiod Location Routing Problem

PCP Prize Collection Problem

SBCP Stochastic Benefit Collection Problem

NGO Non governamental organization

VRP Vehicle Routing Problem

TSP Traveling Salesman Problem

UN United Nations

WHO World Health Organization

PUI Premiére Urgence Internationale

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Introduction

One of the United Nations (UN) 2030 Sustainable Development Goals is to “Ensure healthy lives and promote well-being for all at all ages” (UN, 2015). This goal closely relies on the access to healthcare services. Over the years the World Health Organization (WHO) and its partners have relied on mobile clinics to make healthcare services accessible to populations (WHO, 2016). These efforts are centered on humanitarian and disaster relief. The International Federation of the Red Cross and Red Crescent Societies (IFRC), states that mobile clinics are expensive to operate and their deployment represents a logistical challenge (Du Mortier et al., 2020), which entails the need for better management planning tools. Furthermore, both academics and practitioners have expressed a need for the development of humanitarian logistics and supply chain standards (Paciarotti et al 2021). Hence, practitioners deploying mobile clinics in humanitarian settings have a need for planning tools and methods that would facilitate standardization.

McGowan et al. (2020) define a mobile clinic as a vehicle that transports healthcare providers and equipment to provide ambulatory health services. These clinics are used by various organizations to provide access to a plethora of healthcare services to populations that otherwise would not have easy access to a permanent healthcare facility (McGowan et al., 2020; Du Mortier and Coninx, 2007a). In areas affected by a disaster or a conflict, and in many remote rural areas, mobile clinics are the only way to deliver healthcare services (Du Mortier and Coninx, 2007a; Blackwell and Bosse, 2007; Gibson et al., 2011; Fox-Rushby and Foord, 1996).

Due to the versatility of mobile clinics they can be used in any of the four humanitarian logistics phases (i.e., mitigation, preparedness, response, and recovery) as described by Celik et al. (2012) and summarized in the following.

Mobile Clinics in Mitigation The mitigation phase involves assessing risks and preventing a hazard from becoming a disaster. Mobile clinics may be used for these purposes by offering populations infected by a deadly disease the proper medical treatments to prevent the spread. At the same time, mobile clinics may collect information needed to assess the risks (e.g. number of people affected and the stage of the disease).

Mobile Clinics in Preparedness Preparedness is the strategic planning and execution of actions to facilitate response and recovery. Mobile clinics could be used for preparedness by placing or prepositioning them in places where limited access to healthcare is expected after or during a disaster. However, this may not be feasible for all types of disasters. For example, armed conflicts are very volatile, and it could be difficult to determine with precision the right location as for the people and equipment to not be hindered during the fire exchange.

Mobile Clinics in Response The response phase starts with the planning while the disaster is still ongoing. It includes, as well, the actions taken in the first hours immediately after the disaster. Mobile clinics can be used in this phase given that they can provide healthcare immediately after the disaster has occurred. Providing survivors immediate help that can prove to be crucial. Also, since the mobile clinics can be used to provide a wide variety of healthcare services they can be equipped based on the disaster and most common physical ailment or injury.

Mobile Clinics in Recovery The recovery phase is the longest of the phases and it starts with the operations executed after the immediate effects of the disaster. Mobile clinics may also be implemented in the recovery phase by providing civilians with a source for their routine healthcare services. Mobile clinics can be positioned in this phase as a temporary resource while permanent facilities restore their capacity.

Therefore, mobile clinics can be used in each of the four phases of disaster and humanitarian relief and the methodologies developed in this study can be used on the deployment of mobile clinics in any of the four phases previously discussed. While the methodologies presented in this thesis are general enough to be applied to all phases, our proposed methods were inspired by mobile clinic deployments for recovery after a disaster.

There are many decisions involved in the operations of mobile clinics. These decisions may be taken a priori (i.e., strategic and tactical) and others during the execution of the operations (i.e., operational).

Strategic The first decision is the selection of the targeted population. This selection will dictate the strategic planning of the mobile clinics' operations. By identifying the target population, management can identify what services should and could be provided, the expected demand, and the spread of the population. This means that for an effective deployment, management must gather insights and data. These insights may include but are not limited to: (1) routes available for transportation of the clinic, (2) the number of expected beneficiaries, (3) healthcare needs of the population, and (4) possible deployment sites. Furthermore, at the strategic level the budget must be identified or assigned. The budget will have a direct impact on the resources that can be used during the deployment at both the tactical and operational levels. Also, the available resources will directly impact the relief potential of the deployment as it will dictate the capacity and capability of the relief program. Moreover, at the strategical phase the possible and acceptable actions to take when faced with uncertainty or unforeseen events should be defined.

Tactical After identifying the target population fixing the budgets, gaining insights, and collecting data, management must decide where, when, and how they will send the mobile clinics to the population (i.e., routing and scheduling decisions). This means that at this stage the exact points of departure and arrival as well as the specific population points at which to offer healthcare must be selected. The routes taken to arrive at said destinations must also be decided. Furthermore, the desired frequency of visitation and the number of people to serve at the selected sites should be identified in this stage as well. Furthermore, in preparation for any unforeseen event or uncertainty that would affect the performance of the deployment at this stage the policy or action to be taken in the face of uncertainty must be identified.

Operational As for the operation planning, the day-to-day decisions must be accounted for. If any unforeseen event occurs decisions must be made to ensure the best use of resources. In other words, if any inconvenience is encountered along the way changes must be made on the spot. The latter does not justify the lack of planning. Management may have guidelines instated at this stage that facilitate the decision process in possible worst-case scenarios.

This study focuses on the tactical phase of mobile clinic deployment planning. The thesis also presents insights on the linkages between and mutual impacts of tactical, strategic, and operational planning. This thesis presents and positions in the literature the "*Tactical Planning of Mobile Clinic Operations*". It presents planning methods developed and provides managerial insights obtained on the deployment of mobile clinics for disaster and humanitarian relief. The proposed planning methodologies are tested on real world instances. The thesis is composed of three chapters that contribute to the literature on mobile clinic planning and the operations research and management science (OR/MS) literature, with 60% of the thesis done in collaboration with PUI. In this study we present the work completed thus far on the literature review on mobile clinics for humanitarian relief in conflict zones (*Chapter 1*), the deterministic tactical planning problem (*Chapter 2*), and a tactical planning methodology which explicitly accounts for uncertainty (*Chapter 3*).

Chapter 1: Literature Review on Mobile Clinic Deployments in Conflict Zones

The first chapter of this thesis combines an integrated literature review and an instrumental case study. The literature review is composed of two targeted reviews on conflict zones and mobile clinics to provide insights as the literature is scarce on mobile clinic deployments in conflict zones. The case study describes the process and challenges faced by PUI during a mobile clinic deployment during and after the Iraq War. The purpose of this chapter is to deepen the understanding of the challenges and implications entailed by deploying mobile clinic in conflict zones to reach populations affected by violence and cutoff from healthcare services. This chapter highlights the gaps in literature, such as the need for studies that document mobile clinic deployments to provide relief after complex emergencies and the lack of planning tools and standards for practitioners. Moreover, in this chapter we provide direction for future research to support the development as well as the need for valuable insights and planning support.These findings can be used as a road map for researchers to contribute to the literature on mobile clinic deployments both in conflict zones and other disaster relief operations. This chapter also serves to underscore the importance and contributions to the literature with the tactical planning tools developed in the remaining chapters of this study. Chapter two aims to address the need for a tactical planning tool that can be used by practitioners deploying mobile clinics in a post conflict zone, to select locations, build a schedule, and identify routes. Chapter three contributes with a tactical planning methodology that considers the uncertainty faced in the field and it proposed and evaluates four different policies to counter the effects of uncertainty in the network.

Chapter 2: The Deterministic Tactical Planning Problem

In this chapter, we present the tactical planning problem for mobile clinic deployment in the classical, deterministic context, where decisions are taken based on a single point forecast of future conditions. This problem is modeled as a multiperiod location-routing problem (MLRP). We develop a set-packing formulation and solve it. This study is the first to formulate a multiperiod location-routing problem as a set packing formulation to provide a tactical planning method that can be used to develop a deterministic plan over a planning horizon at the tactical level. The mathematical model proposed seeks to maximize the total benefit, considering both a coverage component (i.e., visiting a location) and a continuity component (i.e, the number of times an individual receives healthcare services). This is the first mathematical model proposed in the healthcare literature that considers benefits to the population and studies both the continuity and coverage components. The proposed tactical planning methodology in this chapter can aid practitioners to identify the frequency of service and identify the appropriate locations to service based on the continuity and coverage component while considering the proper utilization of resources. Results are presented for an application based on PUI operations in Iraq, including sensitivity analyses on the parameters used to model the healthcare benefits. Managerial insights on the impacts of some organizational strategic and tactical decisions, such as the number of mobile clinics and the relative importance given to coverage and continuity of care, are also presented. We show also how the methodology can aid practitioners when deciding how to prioritize continuity versus coverage. Also, it can be employed to justify budget and resource assignments to a deployment project in addition to the development of a tactical plan for the planning horizon.

Chapter 3: Tactical Planning Under Uncertainty

After presenting a deterministic deployment-design planning methodology for practitioners, Chapter 2 focuses on developing a tactical planning method that accounts for the uncertainty faced in the field. In this chapter we consider the uncertainty that arises in the travel time, the usability of roads, and access to locations in humanitarian and disaster relief operations. Moreover, unlike in the previous chapter this one quantifies the benefit offered as a monetary value. The models in chapter three assume a known a single predefined departure point, select communities to be served and associated routing while they account for the need to adjust under uncertainty. We model mobile clinic deployments as a prize collection problem (PCP) in an effort to maximize the benefit offered by mobile clinics while capturing the uncertainty with a two stage stochastic program. This study is the first to propose a two-stage stochastic program to be used to model mobile clinic deployments with a stochastic benefit collection methodology. Also, we propose four strategies to adjust the tactical plan to the new information available at each application occurrence (i.e., recourse policies) and study the effect of each of them on the key performance indicators. For this study, we test the performance of the plan in the context of vaccination campaigns using real world instances from Malawi, Kenya, and Iraq. The methodology can be used for the tactical planning of deployments under uncertainty and can be adapted to other healthcare service campaigns using mobile clinics. Moreover, this study provides insights into the impact of the recourse policies on the performance of mobile clinic deployments.

Organization of the Thesis

The remainder of this thesis is organized by chapters derived from articles. The first chapter *Analysis of Mobile Clinic Deployments in Conflict Zones* presents the literature review on mobile clinics in conflict zones and has been submitted to the Journal of Humanitarian Logistics and Supply Chain Management. The second chapter titled *Mobile clinics deployment for humanitarian relief: A multiperiod location routing problem* presents the proposed methodology for tactical planning of mobile clinics submitted to Computers & Operations Research. The third chapter titled *A Stochastic Prize Collection Methodology for Mobile Clinic Deployment Problem* is under preparation for submission.

Chapter 1

Analysis of Mobile Clinic Deployments in Conflict Zones

1.1 Introduction

The aftermath of armed conflicts (hereinafter conflicts) has resulted in the inception of various humanitarian organizations. For example, the International Red Cross and Red Crescent Movement started in response to the lack of healthcare during the war of Sulferino in 1859 (IFRC, 2016). Similarly, when the United Nations (UN) was created during World War II in 1945, its members highlighted the importance of creating a global health organization to provide humanitarian assistance to those in need and protect human rights (UN, 2015b). Hence, the World Health Organization (WHO) was founded (WHO, 2022b). Yet, scholars of the discipline of humanitarian logistics have "ignored the area of conflicts, wars and complex emergencies"(Altay et al., 2021, p.579). However, authors (Besiou et al., 2021) have address the UN 2030 Sustainable Development Goals (UN, 2015a) disregarding that countries affected by conflicts are less likely to meet these goals (Garry and Checchi, 2020). Furthermore, conflicts drive 80% of all humanitarian needs and up to two thirds of the world's extreme poor are estimated to live in areas that are fragile or affected by conflicts (World Bank, 2022). Addressing healthcare during and after conflict is essential to reach the UN Sustainability Goals (Samman et al., 2018). Although healthcare needs during and after natural disasters and conflicts are similar, differences arise from the political complexities of conflicts, in which civilian populations are targets of war and human rights abuses aggravate health and protection needs (Leaning and Guha-Sapir, 2013). Additionally, people affected by conflicts experience severe public health consequences driven by population displacement, food scarcity, and the collapse of healthcare services, which together give rise to complex humanitarian emergencies (Toole and Waldman, 1997; Vass, 2001). Conflicts have been major causes of ill health and mortality for most of human history (Murray et al., 2002).

Conflict is possible as soon as weapons are available (Smith, 2004) and operating a humanitarian organization in a conflict zone poses its own challenges and limitations. Unfortunately, violence and conflict lasts for long period of times and combatants can target humanitarian organizations or prevent them from accessing certain populations (Beamon and Kotleba, 2006). Humanitarian organizations may face a plethora of risks that force them to yield to the demands of a warring side to obtain security guarantees to help the affected populations (Weil, 2001). Healthcare services are one of the daily operations that is affected by conflicts. Also, conflict reduces access to healthcare by damaging transport and communications channels (Urdal and Che, 2013) and the risk entailed by travel deters people from seeking healthcare due to the dangers and cost (Grundy et al., 2008).

To provide humanitarian healthcare relief, non-governmental organizations (NGOs) employ mobile clinics (Du Mortier and Coninx, 2007b). Mobile clinics are an intermittent modality used to provide ambulatory healthcare and improve access to health (McGowan et al., 2020; Du Mortier and Coninx, 2007b). These mobile clinics aim to give access to essential healthcare to populations who are unable to access permanent health structures (Médecins du Monde, 2017); as such they serve as a temporary solutions for those in need of medical services. Often they consist of vehicles transporting equipment and healthcare providers, who deliver health services at predetermined outreach posts (McGowan et al., 2020). Typically, mobile clinics 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).

The aim of this paper is to analyze the deployment of mobile clinics in conflict zones from an operations management and logistics perspective. Hence, it addresses three research questions:

RQ1. What are the impact and implications of conflicts zones on healthcare access?

RQ2. What are the benefits and challenges arising from the deployment of mobile clinics in conflict zones?

RQ3. What insights and tools can be developed to support mobile clinic deployments?

Consequently, this study is developed through an integrative literature review and an instrumental case study. The integrated literature review targets both conflicts and mobile clinics. The targeted review on conflicts provides context to how operations and logistic decisions are affected during and after a conflict. In addition, it presents the challenges on the healthcare system and impact on the population in conflict and post-conflict zones. This allows to put in perspective the decisions involved during deployments and the various applications. Then, the case study documents the operations and challenges encountered during the Iraq War by Première Urgence Internationale (PUI), an international non-governmental organization (NGO), that deploys mobile clinics to relief suffering of populations affected by humanitarian crises around the world. Finally, this study highlights the insights derived from the literature review and case studies and it provides directions for future research.

This paper is structured as follows. Section 1.2 details the methodology used in this study. Section 1.3 presents the targeted literature review on conflicts and what they entail, highlighting the dreadful consequences on healthcare systems and the health of people living in conflict zones. Section 1.4 provides the targeted literature review on mobile clinics, practices and standards, while underscoring the role mobile clinics play during conflicts. Section 1.5 showcases the case of Iraq, a mobile clinic deployment by PUI during and after the Iraq War. Section 1.6 explores needed tools for practitioners deploying mobile clinics in conflict zones. Section 1.7 presents the conclusions of this study and synthesizes the proposed direction for future research.

1.2 Methodology

This study is developed through an integrated literature review and an instrumental case study. The literature review underscores recent or historically significant research studies as well as field reports (Cooper et al., 2006) to provide perspective on mobile clinic deployments and conflict zones. Furthermore, the case study describes challenges faced, and uses multiple data collection methods (Njie and Asimiran, 2014) to expose the characteristics of a particular case of mobile clinic deployment in a conflict and post-conflict zone. The methodological framework is depicted on Figure 1.1. With the aim of the research being to analyze the deployment of mobile clinics in conflict zones, three research questions were identified. The answers obtained through the methodology described in the following sections (Sections 1.2.1 and 1.2.2) aid in deriving insights related to the decision-making process involved and what key insights and support tools would be helpful for practitioners. We also stress the complexities and challenges phased while deploying mobile clinics during conflict and post-conflict.

The methodology allows to answer the three proposed research questions. RQ1 is answered with the targeted literature review on conflict zones presented in Section 1.3. With the targeted literature review on mobile clinics, presented in Section 1.4, and the case study, in Section 1.5, we answer the RQ2. Finally, in Section 1.6 we answer RQ3.

1.2.1 Integrated Literature Review

Snyder (2019) has identified integrative literature reviews as the adequate tool for authors to combine perspectives and insights. Since the purpose of this paper is to combine per-

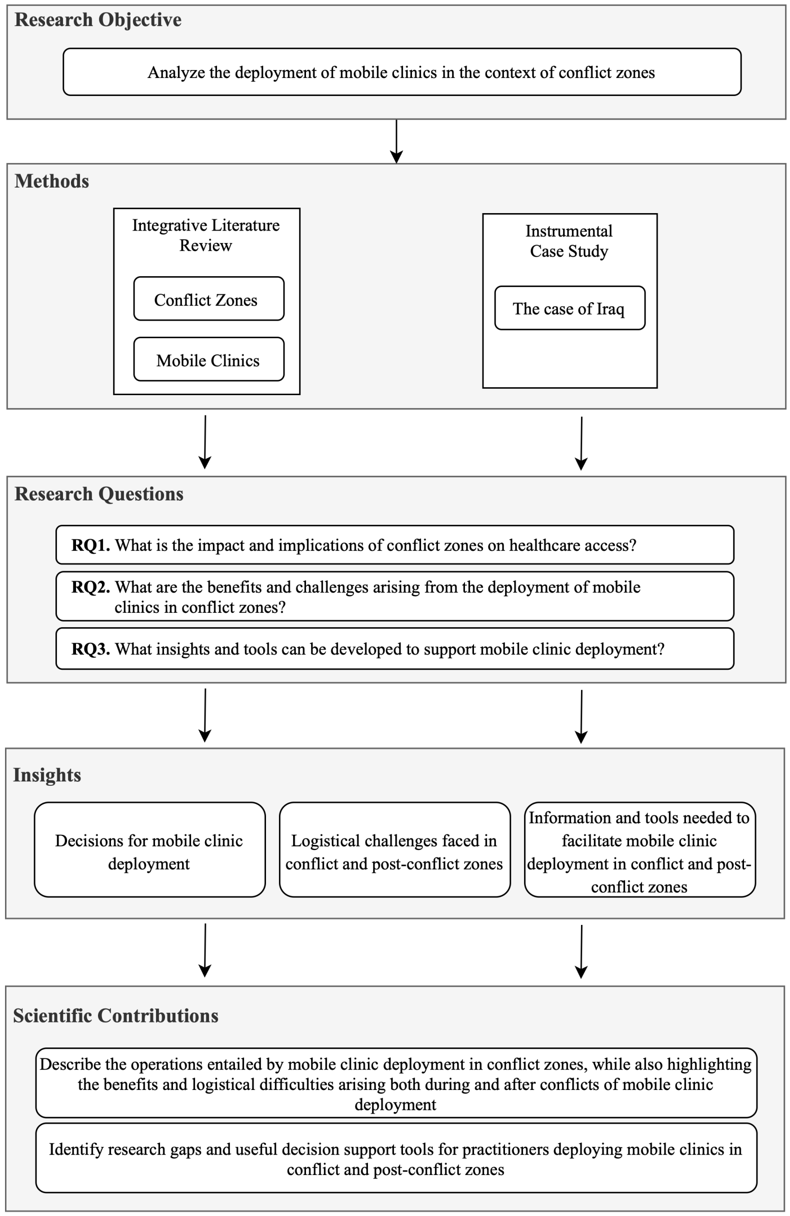


Figure 1.1: Research Methodology, Insights, and Contributions

spectives and information pertinent to the deployment of mobile clinics in conflict and post-conflict zones to answer the research questions, we result to an integrative literature review. In addition, the desired outcome of this study is to provide direction for future research that supports the deployment of mobile clinics. Torraco (2005) stresses that an integrative literature reviews methodology plays an important role in stimulating further research.

Due to the dearth of articles that study the deployment of mobile clinics, the integrative literature review is composed of two targeted literature search (Huelin et al., 2015), i.e., on conflict zones and mobile clinics, conducted in May 2022. The literature search mainly focused on peer reviewed journal publications and, hence, it started by searching for keywords in the ABI/Inform (ProQuest) database. The keywords included "conflict zones", "war zones", "armed forces", "war relief", "humanitarian logistics", "mobile clinics", "mobile health teams", "mobile hospitals", and "mobile health units"(Figure 1.2). Title and abstracts of the resulting articles were analyzed to determine the relevance. This was followed by reference and citation analyses to find related contributions, known as going backwards (Webster and Watson, 2002). In addition, Google Scholar was used to identify articles that cited the relevant literature, known as going forward (Webster and Watson, 2002).

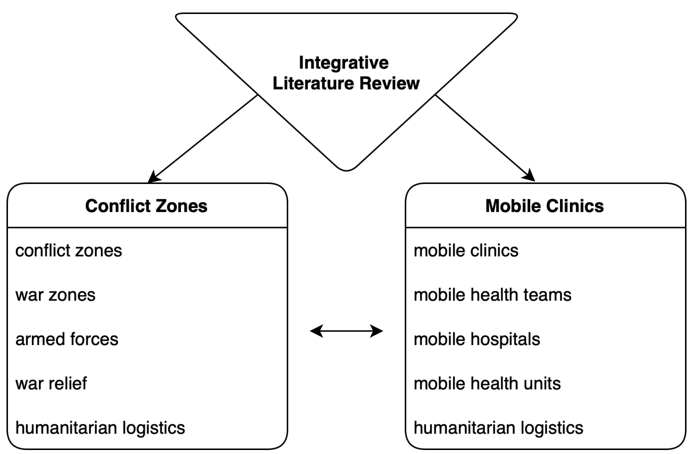


Figure 1.2: Integrative Literature Review

Benzies et al. (2006) encourage authors to result to grey literature when there is little evidence. Hence, the peer reviewed publications are supplemented and synthesized with the use of grey literature. Not only have purely research-based reviews been criticized for their inability to provide meaningful conclusions (Pawson et al., 2005), but also grey literature has been praised for its relevance and likelihood to be more up to date (Rothstein and Hopewell, 2009). To identify the relevant grey literature, the websites and databases of known nongovernmental organizations such as the World Health Organization (WHO), the United Nations (UN), and the International Federation of Red Cross and Red Crescent Societies (IFRC) were used. By including grey literature this study increased the likelihood of a comprehensive search (Benzies et al., 2006).

The findings of the integrated literature review are used to define the peculiarities of mobile clinic deployments in conflict and post-conflict zones. First, the targeted literature review on conflict zones is presented in Section 1.3. It begins by providing the definition of conflict zones, post-conflict zones, and the different degrees of conflicts. Moreover, the targeted review present past historical data and summarize the findings of empirical studies that concentrate on the nature, duration, and onsets of conflicts. Findings by various authors related to the toll of conflict on citizens, their health, and the healthcare systems that serve them and its lingering effect when conflict zones transition into post-conflict zones are discussed. Second, in Section 1.4, the targeted literature review on mobile clinics is presented. Based on empirical studies found in the literature, mobile clinics are positioned as temporary measure to satisfy healthcare requirements of populations affected by conflicts. We also present statistics compiled through the WHO's website on the various deployments of mobile clinics over the years. These statistics serve to further illustrate the importance of research directed towards the development of decision-making tools to support mobile clinic deployments in conflict and post-conflict zones.

1.2.2 Instrumental Case Study

The main goal of a case study is to extract in-depth details about an event, person or process (Njie and Asimiran, 2014). In this case study, the decision process during the mobile clinic deployment in Iraq by PUI, a non for profit and non governmental organization (PUI, 2016b), is documented and described to uncover insights of challenges faced by practitioners. Stake (1995) classifies case studies into three types: intrinsic, instrumental and multiple case studies. Because the case of Iraq is examined to generalize the logistical difficulties and operations entailed in the deployment of mobile clinics in conflict and post-conflict zones, it can be classified as an instrumental case study. The Iraq War ranging from 2003 to 2011 is the bounded context in which the presented case study is depicted (Miles and Huberman, 1994). The case study arises from a series of exchanges between the in field project managers and head medical staff as part of a collaboration between the authors and the organization. The sources used for data collection included interviews, documents, archival records, and observations (Stake, 1995; Yin, 1994; Leedy and Ormrod, 2005). The collaboration was initiated in 2016 and continued until the deployment was phased out in 2019, for a total of three years. Hartley (2004) highlights that case study research "consists of a detailed investigation, often with data collected over a period of time, of phenomena, within their context,"and additionally aims "to provide an analysis of the context and processes which illuminate the theoretical issues being studied"(p. 323).

1.3 Conflict Zones

To fully grasp what it means to deploy mobile clinics in conflict zones one must understand the nature and the implications of conflicts. The aim of this targeted literature review, is to provide a general understanding of the characteristics of conflict zones and the effect on the territories they take place in. To answer RQ1, we concentrate on how conflicts affect the access to healthcare and the health of the populations. We start by adhering to the definition of conflicts as presented in the literature and providing a brief historical overview of documented conflicts in Section 1.3.1. Then, in Section 1.3.2 we discuss the literature that studies the effects of conflicts. In Section 1.3.3 the particular healthcare implications of conflicts on the populations affected are exposed. Finally, this information is used to position the role of mobile clinic deployments in both conflict and post-conflict zones in Section 1.3.4.

1.3.1 Armed conflicts

Pettersson and Wallensteen (2015) define conflicts as the "contested incompatibility that concerns government and/or territory where the use of arm force between two parties, of which at least one is the government of a state, results in at least 25 deaths must be recorded during battle"(p. 536). The same authors defined arm force as the use of any materials (e.g., manufactured weapons, sticks, stones, water) to promote the parties' general position and resulting in deaths. Herein, conflict zones are the geographical territories in which conflicts take place. Wallensteen and Sollenberg (2000) defined four types of conflicts; minor conflicts, intermediate conflicts, wars, and major conflicts, all defined by the number of deaths (Figure 1.3).

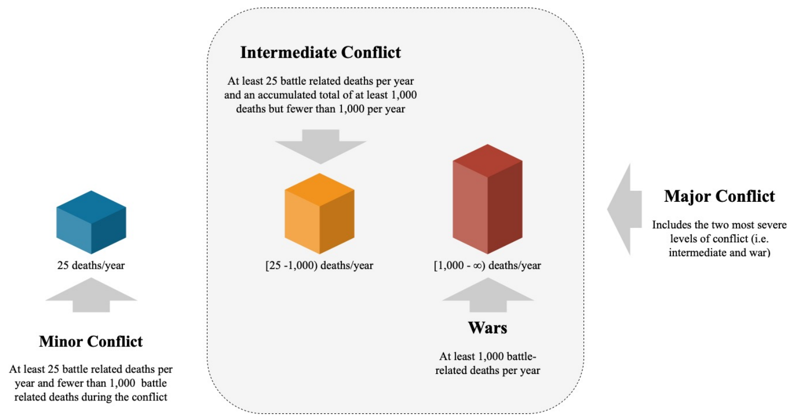


Figure 1.3: Types of Conflicts, adapted from Wallensteen and Sollenberg (2000)

The historical occurrences of conflicts has been well studied and documented (Smith, 2004; Themnér and Wallensteen, 2011; Cederman and Weidmann, 2017; Pettersson and Wallensteen, 2015; Strand et al., 2020; Strand and Hegre, 2021). Cederman and Weidmann (2017) stress the importance of documenting conflicts and, thus, initiated the movement of the Uppsala Conflict Data Program (UCDP). The UCDP database contains a comprehensive number of data files with historical data on different conflicts around the world starting from the year 1939 registering a total of 2,506 conflicts (see Figure 1.4). Authors could not find any significant evidence to indicate that conflicts would continue to decrease in upcoming years (Kreutz, 2010; Strand and Hegre, 2021). Cederman and

Weidmann (2017) points out that the occurrence, location, frequencies, and termination of conflicts are hard to forecast. Smith (2004) highlights that a combination of poor economic conditions, political repression, and degradation of renewable resources are a catalyst for conflicts.

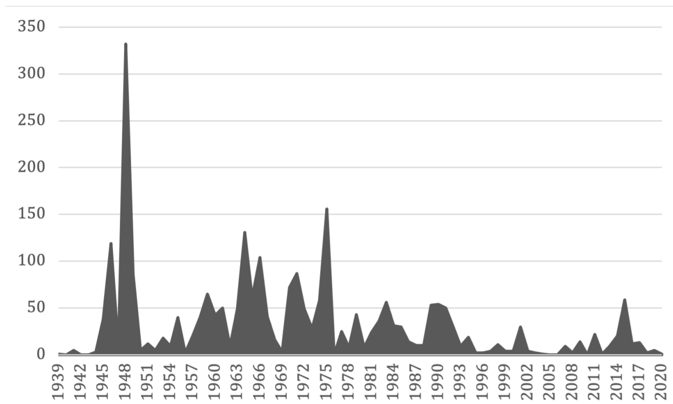


Figure 1.4: Conflicts Started from 1939 to 2020, source: Pettersson (2021)

Kreutz (2010) found that the terminations of conflicts involved peace agreement, ceasefire, victory or others. Conflicts ending in victory had the shortest duration, approximately a year and seven months, while conflicts ending with a cease fire lasted the longest, approximately four years and nine months. Kreutz (2010) also found that external peace keeping efforts were significant to prevent a resumption of conflict after a continuous year of conflict. This displays the importance of the “Genocide Prevention and Responsibility to Protect ”adopted in 2005 by the UN to motivate states to intervene in conflicts that endanger civilians (UN, 2019).

1.3.2 Consequences of Conflicts and Humanitarian Needs

Conflicts have dreadful consequences on populations. The exposure to conflict zones creates economic, social, ecological, psychological, and nutritional stressors (Clarkin, 2019). Apprehension and exposure often lead to the displacement of population as people seek refuge and help, sometimes moving across borders. The United Nations High Commissioner for Refugees (UNHCR) identified 53.2 million forcibly displaced people in 2020, as a result from persecution, conflict, violence or human rights violations (UNHCR, 2021). Displaced populations often suffer from lost property or social capital, resettlement in less fertile areas, restricted mobility, and are often viewed as a burden for their hosts (Al Gasseer et al., 2004; Hynes and Cardozo, 2000; Salama et al., 2004). Clarkin (2019) remarks that those that remain tend to fare worse than those who cross an international border.

Civilians are subjected to wartime violence during conflicts due to various factors. Hovil and Werker (2005) found that civilians were targeted as a display of commitment to continue fighting. Researchers have observed that groups that receive support from foreign governments have few to no incentives to refrain from attacks against civilians (Salehyan et al., 2014; Toft and Zhukov, 2015; Weinstein, 2006; Zhukov, 2017). Even in a post-conflict context the resentment towards groups that have collaborated with enemies can lead to ethnic violence (Bell-Fialkoff, 1993; Taras and Ganguly, 2015) and towards revenge (Weidmann, 2011; Balcells, 2010; Gibbs, 2018). However, Azam (2002) posits that violence against civilians is a byproduct of looting and resource competition. This goes in line with the observations of Koren and Bagozzi (2017), which found higher incidents of violence against civilians in areas with more agricultural resources, as governments and rebel groups compete for access to food. During conflicts fighters engage in sustained looting against their own communities and hold roadblocks for ransom (Englebert and Ron, 2004).

Conflicts often conserve gender roles (Bjarnegård et al., 2015) and have different effects among age and gender groups in the population. For instance, the majority of active combatants are males (Henshaw, 2013), which explains why men are at a higher risk of death (Zwierzchowski and Tabeau, 2010). Women are often subjected to wartime violence such as sexual exploitation (Centre, 2005). Messer et al. (2001) found that during conflicts children are subjected to homelessness and separation from community ties. Most often, “breadwinners’are the ones who fall victim to landmines (Messer et al., 2001).

The use of landmines can hinder farming, avert economic development, and also lead to casualties even decades after a conflict has concluded (Khamvongsa and Russell, 2009).

Moreover, shelling and bombing can disrupt topography, form craters, and alter drainage patterns (Hupy and Schaetzl, 2006). Additionally, in conflict zones there's a reduction in access to water and sanitation services, which in turns increases poverty (Gleick, 2019). Garfinkel and Skaperdas (2007) found that valuable resources are diverted away from investment and consumption and instead go directly into obtaining arms and, thus, there is a significant reduction in trade and an increase accumulation of productive capital. Moreover, the insecurity posed by conflicts deter trade activities across national borders leading people to participate instead in less productive and more secure activities (Garfinkel and Skaperdas, 2007). Addison et al. (2001) signals that post-conflict economies have weak regulatory authorities, and financial system becomes loaded with unsound loans, this leads to problems that can endanger economic recovery and peace. Hence, conflicts pose development hardships for citizens and a high cost on the international community (Ross, 2003).

The horrific consequences of conflicts, both on soldiers and civilians, have shaped humanitarian aid into the systems we see today, even leading to the conception of the humanitarian principles (Rysaback-Smith, 2015; Macintosh, 2000). During conflicts, foreign donors attempt to alleviate the suffering by sponsoring humanitarian aid (Wood and Sullivan, 2015). To the point where humanitarian aid has become an essential component of the international community's response to conflicts and humanitarian organizations have taken an active role by providing vital services and security to internally displaced people (Anderson et al., 1999; Duffield, 1997). Although Wood and Sullivan (2015) points out that humanitarian aid may produce short-term instability and increased violence by encouraging both rebel and government forces to engage in violence against civilians, it remains essential to save lives and help people to enjoy the most basic rights to shelter, water, and enough to eat (Bryer and Cairns, 1997).

1.3.3 Healthcare Implications

Frost et al. (2017) noted that the most common injury sustained during conflicts was a limb amputation. Severe disabilities can be attributed to landmines during and post-conflicts (Coupland and Korver, 1991). McPherson (2019) noted that traumatic brain injuries among the population suggest they are caused by landmines and explosive devices, and are further associated with mental health concerns. Violence has also major effects on physical and mental health, including injuries from rape, HIV, reproductive health problems, and social isolation (Spangaro et al., 2013; Stark and Ager, 2011). Moreover, the physical injuries and health effects last into older age and are usually worse for older women versus for older men (Ghobarah et al., 2004; Massey et al., 2017). Also, populations affected by conflicts often suffer mental health disorders such as post-traumatic stress disorder, stress, insomnia, anxiety and depression (Garry and Checchi, 2020).

Leaning and Guha-Sapir (2013) posit that the main health implications of internal conflicts are not combat-related injuries and deaths. However, Murray et al. (2002) highlights that quantifying the health implications of conflict is challenging due to the fact that civil registration systems, often cease to function during conflicts. Levy and Sidel (2016) identifies a need for an independent, nonpartisan mechanism, established and maintained by a UN agency or a multilateral organization, to investigate, document, and report on health consequences of conflict. Nonetheless, numerous studies have documented the gruesome implications of conflicts on the health of populations affected with the use of surveys, news reports and external data bases. Ghobarah et al. (2003) found that conflicts deepen the risk of death and disability with increases in homicide, transportation accidents, other injuries, and cervical cancer. Wise and Barry (2017) underscored the prevalence of disease outbreaks in conflict zones. Jawad et al. (2019) found evidence that associates conflicts with an increased coronary heart disease, cerebrovascular and endocrine diseases, in addition to increased blood pressure, lipids, alcohol and tobacco use. Kimbrough et al. (2012) noticed that incidence and prevalence of tuberculosis was twice more as high in conflict-affected populations. The challenging environments, including attacks on health workers, mean that vaccination and eradication campaigns repeatedly fail to achieve sufficient coverage in conflict zones (Bhutta, 2013; Morales et al., 2016; Wise and Barry, 2017). Additionally, poor access to healthcare and lack of continuity of care during conflict has resulted in a disruption to the effective care of cardiovascular and cerebrovascular conditions, diabetes, chronic respiratory diseases, cancers, and other non communicable diseases (Bendavid et al., 2021).

The healthcare implications on women and children have been extensively studied. Rai et al. (2019) documented that conflict and emergencies contribute to the mortality and long-term health deterioration for females. Wagner et al. (2019) observed an increase in maternal mortality that is directly correlated to the intensity of the conflict. Bendavid et al. (2021) saw an increase in the probability of dying in women of childbearing age when exposed to conflict. This could be attributed to the reduced access to maternal and newborn health services, especially for the poorest and least educated women (Gopalan et al., 2017; Akseer et al., 2020). It was observed that conflict exposure decreases fertility based on studies in Angola, Ethiopia, and Eritrea (Agadjanian and Prata, 2002; Lindstrom and Berhanu, 1999; Blanc, 2004). Additionally, two studies observed the unmet need for family planning in conflict settings (McGinn et al., 2011; Ivanova et al., 2018). Maternal mortality tends to worsens in conflict zones (Alkema et al., 2016; Kotsadam and Østby, 2019). When it comes to children, Wagner et al. (2018) found that infants exposed to conflict in their first year had a higher chance of dying before their first year. Keasley et al. (2017) points out the significant relationship between exposure to conflict and a detrimental effect on birth weight. Four studies demonstrated a statistically significant increase in premature births due to conflict exposure (Arnetz et al., 2013; Bodalal et al., 2014; Skokić et al., 2006; Keren et al., 2015). Additionally, Bendavid et al. (2021) noted that chronic malnutrition in children are more pronounced among children near conflict zones. Qadri et al. (2017) attributed the cholera outbreak in Yemen to the bombing of water facilities. All these implications obviously lead to a need for humanitarian healthcare.

1.3.4 Humanitarian Healthcare in Conflict Zones

Since the adoption of the UN's "Genocide Prevention and Responsibility to Protect", efforts to send humanitarian aid to conflict zones has increased (Bellamy, 2015). Leaning and Guha-Sapir (2013) states that public health is a major component of the larger operational framework of international relief. Public health encompasses disease control, reproductive health and maternal care, psychosocial support, short-term or emergency medical and surgical interventions, and sanitation and nutritional services (Leaning and Guha-Sapir, 2013). Evidence has been found that supports the role of public health measures for peace building (Sen and Faisal, 2015) and social cohesion (Kruk et al., 2010) in the after-math of a conflict. Authors have documented cases where access to healthcare services has improved compared with pre-conflict due to humanitarian and international aid (Gordon et al., 2010; Gates et al., 2010). Devkota and van Teijlingen (2010) state that the international community should continue and increase their support to strengthen the health sector of territories affected by conflicts.

During a conflict, the infrastructure, including buildings, medication stores, laboratories, electricity and water, may be directly targeted or looted (Gordon et al., 2010; Guha-Sapir and van Panhuis, 2002; Gates et al., 2010; Zwi and Ugalde, 1989; Levy, 2002). Health services are often severely interrupted by the destruction of infrastructure and management systems (Ahamadani et al., 2014). Continuity of care is especially difficult in the face of health system disruption and health outcomes are sensitive to healthcare continuity (Buvinic et al., 2013; Aebischer Perone et al., 2017; Isreb et al., 2016). Rubenstein and Bittle (2010) found that despite international humanitarian laws, medical personnel and wounded are targeted during conflicts and some countries have laws that allow the attack of medical facilities if it guarantees a military advantage for the government. Also, they highlight that the non-governmental party involved in the conflict often targets medical personnel to gain grounds on the government. Coupland (1994) posits that medical personnel in conflict zones face stressful situations that demand experience and seasoned judgment beyond medical skills. Stressful exposure often leads the medical personnel to flee the country (Rubenstein and Bittle, 2010).

Humanitarian organizations are challenged with how to effectively tackle the need for healthcare to treat diseases during conflicts and into post-conflict (Jawad et al., 2019). Practitioners are constantly faced with a lack of historical information on chronic illnesses of the people affected by conflicts (Aebischer Perone et al., 2017; Massey et al., 2017; Owoaje et al., 2016). The personnel also faces political and military barriers that hinder the delivery of humane and appropriate care (Weindling, 1998). In the midst of a conflict, international standards are difficult to adhere, due to risks of those who provide information and who collect it (Ford et al., 2009). Morgan et al. (2006) noted that while delivering aid broader societal issues related to humanitarian response can be neglected, such as the need to maintain respect for cultural practices regarding death and grief. Also, Iserson and Moskop (2007) signal that delivering medical aid can require population-based triage decisions that are technically complex and morally challenging. Training healthcare professionals to deliver interventions during and post-conflict and ensuring continuity in the supply of common medications are key priorities (Jawad et al., 2019). After surveying the literature on humanitarian operations that take place in conflict zones, one can conclude that offering relief in a conflict or post-conflict zone comes with its complications. In fact, practitioners cannot simply replicate standard practices previously identified and successfully implemented in other humanitarian contexts and often will not even be able to replicate practices implemented in other conflict zones. Conflict and post-conflict zones require adapting practices to address what is found in the field and, as documented in the literature, often this is not known until the relief operation begins.

1.4 Mobile Clinics

Based on the complexity conflict zones inflict on humanitarian healthcare delivery, mobile clinics are a valuable resource. Understanding how mobile clinics fit into humanitarian healthcare delivery in a conflict zone requires to know what a mobile clinic is and how practitioners have used them. Hence, this section, as part of the integrative literature review, presents a general definition of mobile clinics, discusses practitioner's materials and guidelines designed to facilitate the decision making process, and provides a general overview of various deployments that have taken place in conflict zones. Due to the dearth of literature documenting mobile clinic deployments in conflict zones, we supplement the overview with literature pertaining to deployments outside conflict zones. First, we describe what mobile clinics are based on the available academic and grey literature in Section 1.4.1. Then, we discuss the benefits and challenges of mobile clinic deployment in Section 1.4.2, and more specifically in conflict zones Section 1.4.3. This allows to answer RQ2 and RQ3 and derive specific insights on mobile clinic deployments.

1.4.1 What are mobile clinics?

Mobile Clinics (*a.k.a.* mobile health units, mobile health teams, or mobile hospitals) are an intermittent modality used to provide ambulatory health services and improve access to the healthcare (McGowan et al., 2020; Du Mortier and Coninx, 2007b). Malone et al. (2020) further defined mobile clinics as customized motor vehicles that travel to communities to provide healthcare. However, this vehicle does not necessarily have to be customized as long as it can transport equipment and healthcare providers to a predetermined outreach post where services will be delivered (McGowan et al., 2020). Mobile clinics can take various shapes or forms, for example it could be on a boat (WHO, 2022a), it can be on a modified vehicle (Harneis, 2016; Isha Outreach, 2021), or it can be transported in a vehicle but use an existing facility (Unmeer, 2015) or just a set of tables (Harneis, 2016). On our search we found that the earliest documented (i.e., photographed) mobile clinic was used by the Department of Health in Gaza back 1939 (Picryl, 1939)

The intent of deploying mobile clinics is to promote the access to healthcare (ICRC, 2006; Du Mortier and Coninx, 2007a) by providing primary healthcare services, with the possibility of referral to nearby fixed structures for conditions not manageable with the resources of a mobile clinic (McGowan et al., 2020). McGowan et al. (2020) also state that mobile clinics are better suited to offer preventive services, such as vaccination or antenatal care, or outpatient-level case management of chronic conditions, including mental health problems, high-burden non-communicable diseases, among others. Moreover, Du Mortier and Coninx (2007a) underscore that mobile clinics should be used as an exceptional modality, only deployed as a "last resort" to reach populations cut off from health services. However, in some cases mobile clinics are the only way to deliver humanitarian healthcare (Du Mortier and Coninx, 2007b; Blackwell and Bosse, 2007; Gibson et al., 2011; Fox-Rushby and Foord, 1996). The WHO has referred to mobile clinics as an exemplification of the tension between equity of healthcare access and the efficient utilization of scarce resources (de Roodenbeke et al., 2011). Mobile clinics through the literature and documented deployments have been shown to be an effective method to deliver healthcare interventions and outreach activities (Shaikh, 2008). Hence, why mobile clinics are a common modality for delivering health services in humanitarian emergencies, including conflict zones (McGowan et al., 2020).

1.4.2 Mobile Clinic Deployments: Benefits and Challenges

In order to provide an understanding of the activities of mobile clinics in conflict zones for humanitarian healthcare, we explore practitioner's materials and guidelines. Although practitioner's material on mobile clinic management is readily available, it mainly focuses on medical interventions. In an effort to sets out directives relating to the use of mobile clinics, the International Committee of the Red Cross (ICRC) put forward a document in 2006 with specific guidelines for mobile clinics. In this document they go beyond specific health program considerations and discuss general management, which include logistics issues (ICRC, 2006). The document highlights the difficulties faced by practitioners due to standards imposed by local authorities and the necessity to correctly estimate needs at the locations mobile clinics will be deployed. Later on, in 2007, the Humanitarian Practice Network at the Overseas Development Institute commissioned another document to aid practitioners when deploying mobile clinics in emergency contexts (Du Mortier and Coninx, 2007a). Other guides have been developed by health ministries, health clusters, and practitioners in the international community, such as Gui (2014), Health and NUT Cluster - Iraq (2014), National Health Mission Manipur (2012). However, these offer specific guidelines addressing the communities and adhering to the respective Ministry of Health (MoH) regulations. Hence, in this section we concentrate on the ICRC's and

Overseas Development Institute's guides.

In their guide, the ICRC states that mobile clinic interventions are: "[...] an exceptional strategy, to be used only as a last resort with the aim of providing health services to population groups which have no access to a health-care system."(ICRC, 2006, p. 6). Du Mortier and Coninx (2007a) state that mobile clinics "are often used to provide healthcare in unstable situations, such as conflicts, where fixed services cannot function for reasons of security"(p. 1). Moreover, the ICRC states that the temporary nature of mobile clinics mixed with logistical challenges (e.g., distances to be traveled, the time required, rises in water levels, weather conditions) and security challenges (e.g., agreements, checkpoints) restrict practitioners to a very limited decision time frame.

Throughout both guides the importance of planning (e.g., mode of action, human and material resources, time frame and logistics) and selecting services that will be offered (e.g., vaccination, health promotion, preventive activities, transfer of patients, curative care), is stressed. Additionally, both guides breakdown the decision process of mobile clinic deployments into eight key questions. These questions aim to find answers to strategical, tactical, and operational decisions (Figure 1.5). During the strategic phase, decision makers must select areas (i.e., conflict or post-conflict zones) that will receive healthcare services. They must also determine the appropriate number of mobile clinics, healthcare practitioners, and medical equipment, as well as the available budget (ICRC, 2006; Du Mortier and Coninx, 2007a). As for the tactical decisions, practitioners must schedule the mobile clinics, and also decide on the frequency of visits, the days, and the time of day to deploy the mobile clinics to each location in accordance to the strategical decisions. Additionally, depending on the healthcare condition of the patients, more than one visit may be needed to provide the required healthcare. Finally, the operational phase consists of implementing the plan and evaluating the performance, i.e., action reports (ICRC, 2006; Du Mortier and Coninx, 2007a).

Du Mortier and Coninx (2007a) also provide some insights and guidelines when deploying in conflict zones. They state that mobile clinics are a way of gaining protection for the populations as part of the organizations' activities by virtue of the Statutes of the

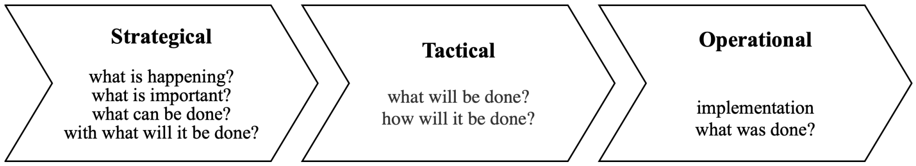


Figure 1.5: Questions to Answer During the Decision Process for Mobile Clinic Deployments, adapted from Du Mortier and Coninx (2007a)

ICRC Movement (Article 5.2, paras c and d) (ICRC at Geneva, 1986). In addition to providing healthcare, mobile clinic deployments in conflict zones can be used to document alleged abuses and make contact with armed groups involved in the conflict. It is important that healthcare workers are well-informed of both the health and the protection objectives of their work in conflict zones. Furthermore, the WHO refers to mobile clinics as an alternative to provide healthcare in their guide for medical care in insecure environments (WHO, 2021). The WHO's guide highlights the importance of coordination to ensure equity across communities, with no missed or under served communities, and easy to reach communities not over served by multiple and potentially contradictory medical visits. It also states the importance of logistics to ensure mobility during conflicts to avoid targeted attacks to the personnel and beneficiaries in conflict zones.

Authors have documented how mobile clinics can be used to overcome common access barriers such as time, geography, system complexity, and trust, and how they result in improvements in health outcomes and reductions in costs (Oriol et al., 2009; Malone, 2010; Song et al., 2013; Brown-Connolly et al., 2014; Drake et al., 2015; Taylor et al., 2016; Malone et al., 2020). McGowan et al. (2020) points out that mobile clinics can be efficient, effective, and can be used to increase service coverage. Authors have also studied contexts in which mobile clinics play an integral part in a healthcare system, providing accessible and sustainable care with quality that matches traditional healthcare settings (Edgerley et al., 2007; Guruge et al., 2010; Iredale et al., 2011; Guruge et al., 2010). Other studies have also shown that mobile clinics can produce both cost savings and improved health outcomes (Chen et al., 2020; Hill et al., 2014; Song et al., 2013; Yu et al., 2017). Mobile clinics are also associated with cost savings generated by effective prevention (Ali, 2022). They allow for quick response and flexibility due to their ability to change locations (Wray et al., 1999), and they can be equipped to respond to several issues (Blackwell and Bosse, 2007). Campos and Olmstead-Rose (2012) have highlighted the fact that mobile clinics are extremely effective in offering urgent care, providing preventative screenings, and initiating chronic disease management. Krol et al. (2007) sustain that another advantage of mobile clinics lies in the ability to provide a diversity of services for various groups, such as people with social problems in both urban and rural areas, at all levels and for acute and chronic diseases. Patients have reported that mobile clinics as an alternative to other healthcare models help them navigate the more convoluted systems of the wider healthcare system and allow them to connect with the medical and social resources in their communities (Aung et al., 2015; Rodriguez et al., 2007). Also, mobile clinic patients have reported an increased sense of self-confidence and ability to manage their chronic conditions (Aung et al., 2015; Hill et al., 2012; de Jesus Diaz-Perez et al., 2004; Jani et al., 2012). The use of mobile clinics can improve the overall quality of medical services and access to basic medical needs (Aljasir and Alghamdi, 2010). Mobile clinics can improve health situation in locations where they are used for screening and prevention (Prasad et al., 2008). They also have been effective in preventing hospitalizations (Guo et al., 2001). Moreover, they provide underprivileged patients with access to better healthcare and medical equipment (ICRC, 2006). In rural areas, due to the quality and conditions of roads and lack of proper transportation, there is a need for mobile clinics to provide healthcare to populations that need constant medical attention, such as elderly patients, pregnant women, and children (Aljasir and Alghamdi, 2010). Hence, the main customers of these mobile clinics include people living in areas that lack proper healthcare infrastructure, such as conflict and post-conflict zones, or those who are not able to seek medical attention at a different location (Aljasir and Alghamdi, 2010). Mobile clinics can also encourage vulnerable populations to seek their needed healthcare by removing the difficulties of scheduling an appointment, long waiting lines, and a complex administrative process (Campos and Olmstead-Rose, 2012; Diao et al., 2016; de Jesus Diaz-Perez et al., 2004; Dasgupta et al., 2015; Kennedy et al., 2014;

Harris et al., 2011). Furthermore, the literature supports mobile clinics as a successful and cost-effective model of healthcare delivery uniquely positioned to assess and fulfill the needs of under served populations (Yu et al., 2017).

On the downside, mobile clinics are expensive compared to other delivery strategies, logistically onerous, time-inefficient (due to medical resources remaining idle throughout a substantial travel time), and in addition they rarely demonstrate a lasting impact (Du Mortier and Coninx, 2007a; ICRC, 2006; de Roodenbeke et al., 2011). Due to sustainability issues and typically low frequency of visits, mobile clinics may not be capable to fully address chronic diseases and acute illnesses (McGowan et al., 2020). Kohli et al. (2012) observed that mobile clinics do not perform better than fixed facilities and, thus, highlight the importance of only using them as an exception in the absence of a permanent healthcare facility (ICRC, 2006). Krol et al. (2007) also point out that sometimes the population may show unwillingness to use the services provided by mobile clinics. In remote communities (e.g., conflict zones, refugee camps), mobile clinics attract large numbers of people, which in turn creates a considerable risk of more infections (McGowan et al., 2020). Other weaknesses of mobile clinics include repeated changes in macro level of medical policies, lack of sufficient feasibility evidence, presence of interfering factors (e.g., other healthcare institutions), potential lack of government's commitment in funding and improper distribution of resources, absence of planning about periodical evaluation, insufficient equipment for disabled patients, scarcity of dedicated funding and professional personnel (Song et al., 2013; Prasad et al., 2008; Al-Attar, 10). Also, it is costly to train the medical personnel of a mobile clinic (Fox-Rushby and Foord, 1996). Lehoux et al. (2007) point out that since mobile clinics tend to be temporary there is a dearth of documentation. In addition, authors have observed that there can be clashes of authority between nurses and doctors due to the lack of documented procedures for mobile clinics (Fox-Rushby and Foord, 1996; Lehoux et al., 2007). Additionally, after deploying mobile clinics for various decades, WHO practitioners believe their weaknesses arise in the reliability, with humanitarian intervention experts expressing concerns regarding the fact that mobile clinics tend to break down and run out of gas (Ali, 2022), depending on the setting (e.g., in a conflict zone) this can be an insurmountable complication. Regardless of these drawbacks, the WHO endorses the use of mobile clinics for humanitarian crises by agencies and donors who are eager to support their implementation (WHO, 2016b).

1.4.3 Deployments in conflict zones

Despite decades of humanitarian healthcare delivery with mobile clinic deployments (Ali, 2022), there are limited studies on the use of mobile clinics in humanitarian responses (McGowan et al., 2020). Most studies found relating to mobile clinics take place outside conflict zones and the majority of the peer reviewed literature is on mobile clinics deployed in the United States (Yu et al., 2017). In recent years mobile clinics have become increasingly visible due to the COVID-19 pandemic as they are well suited to fill healthcare needs during an epidemic (Ali, 2022; Alcendor et al., 2022; Levy et al., 2021; Leibowitz et al., 2021). Authors have also documented the usefulness of mobile clinics to target under privileged populations (Wray et al., 1999; Blackwell and Bosse, 2007; Whelan et al., 2010; Aljasir and Alghamdi, 2010; Gibson et al., 2011; Limaye et al., 2018; Beks et al., 2020; Guillot-Wright et al., 2022; Breve et al., 2022) . Mobile clinics are suitable for various uses and situations (Samakouri et al., 2022; Murphy et al., 2000; Phillips et al., 2017) with the necessary equipment and medical personnel (Hill et al., 2012). McGowan et al. (2020) highlight that they may function in tandem with, and in support existing provider (i.e., community health workers, hospitals, clinics) to further extend access to services. Mobile clinics have become increasingly visible in less fraught settings they are a familiar sight in conflict zones (Ali, 2022). They can be used to provide a plethora of healthcare services that are needed by population in conflict and post-conflict zones.

Despite a paucity of peer-reviewed articles documenting and studying mobile clinic deployments in conflict zones, international humanitarian organizations continue to report the use of mobile clinics to serve populations affected by conflicts. In 2020, MSF reported mobile clinics deployments in 23 countries with 13 of these deployments in countries being affected by conflicts (MSF, 2021). In 2021, the ICRC reported a total of 21 million doses of COVID-19 vaccines administered by mobile clinics in areas impacted by conflicts (ICRC, 2022).

Table 1.1: Healthcare Services Delivered by Mobile Clinics

Service	**Number of Projects**
General health services	98
Outreach	53
Primary healthcare	113
Preventive action	51
Health promotion	23
Curative care	17
Sum of Referrals	22
Mental health	37
Food security	19
Social services	41
Emergency health services	6
Staff training	169

In order to analyze the mobile clinics practices by humanitarian organizations in a conflict setting, a data extraction of projects plans submitted by humanitarian organizations for funding, which included mobile health clinics, was made using the database of the Financial Tracking Service (FTS) of the UN's Office for the Coordination of Humanitarian Affairs (FTS, 2022). The search was conducted on submissions made between 2009 and 2021, for a total of twelve years. The inclusion criteria included the keywords: "mobile health team*"or "mobile clinic*"or "mobile hospital*". This led to a first selection of 395 projects. Further coding was done to keep only projects that were involved in conflict zones for a final selection of 209 projects. Of these 209 projects, only 93 used mobile clinics as the exclusive aid delivery method with all other projects including another type of medical activities along with the mobile clinics. This confirms the notion put forward that mobile clinics in a health response need to be used in conjunction with a fixed facility (ICRC, 2006). The WHO also highlights the importance of using fixed medical facilities to support mobile clinics in creating sustainable outreach services (SOS): "The logistics base of these teams, or the "hubs" of SOS, will have to be equipped for transport and equipment maintenance and for supplies storage. SOS Hubs may be established at district or regional health offices or at strategic points, such as rural hospitals where there is electricity for the cold chain, secure storage and transport maintenance facilities, and reliable telecommunications"(Department of vaccines and biologicals, 2000, p. 18). The projects' activity descriptions were further coded to identify the characteristics of services offered by mobile clinics in the project plans. These projects are not necessarily in conflict zones and even though mobile clinics are used other healthcare delivery methods are also employed. Table 1.1 highlights the type of healthcare services linked to mobile clinics according to the number of projects for which they are found. The most common healthcare services for humanitarian relief offered with mobile clinics included staff training, primary healthcare services, and general health services. These findings align with the healthcare services populations seek when in a conflict zone (as seen in Section 1.3) since there are usually no permanent facilities that offer primary care or general services and medical personnel is scarce.

1.5 The case of PUI in Iraq

This instrumental case study aims to derive insights pertaining to logistical difficulties and operations entailed in the deployment of mobile clinics in conflict and post-conflict zones by examining the deployment of mobile clinics by PUI in Iraq. Mobile clinics have been deployed by the MoH and their partners, including PUI, in response to the Iraq War since 2014 (Iraq Health Cluster, 2014). To understand the motivation and reasoning behind PUI's deployment in Iraq, we must explore the nature of the Iraq War as well as the foundations and decision making process of PUI. Therefore, in this section we start with an overview of PUI's organization and presence in humanitarian relief. This is followed by a briefing of the origins and events of the Iraq War and it's effect on the health. Then, we fully describe the mobile clinic deployment in Iraq based on the exchange between the authors and PUI's staff. These conversations and exchanges took place between 2016 and 2018. It included interviews with two project managers, two head nurses, and three headquarters staff members. By describing PUI's deployment during and after the Iraq War we provide a complete description of the operations entailed in mobile clinic deployments in conflict zones. Hence, this section seeks to complement the answer to RQ2.

1.5.1 Mobile Clinic Deployment in Iraq by PUI

For more than 20 years, PUI has carried out humanitarian work in 38 countries, in areas affected by conflicts, natural disasters, and forgotten crises (PUI, 2022). As of 2022, 15 of their missions included the deployment of mobile clinics that directly benefited populations affected by conflicts (PUI, 2022) including missions in Ukraine, Mali, Libia, Niger, Yemen, and Iraq. In 2014, the deteriorating humanitarian situation resulting from an ongoing conflict, internal displacement of population, and an influx of Syrian refugees, forced the health cluster in Iraq to address the lack of healthcare access in hard to reach areas and the added burden on existing healthcare facilities with mobile clinics (Iraq Health Cluster, 2014). PUI was one of various non-governmental organizations that participated as a partner of the health cluster and took on the delivery of primary healthcare and mental health services in various regions of Iraq (PUI, 2016b).

Iraq had suffered 40 years of continual conflict that has had severe consequences on the population's health and the Iraqi health systems and infrastructure (Lafta and Al-Nuaimi, 2019). On top of the immediate casualties, the widespread violence in Iraq created long-term circumstances that affected the population's health through disruption of access to healthcare, as well as the availability of medicines, transportation, safe water supply, sewage disposal, electricity and other infrastructure components (Lafta and Al-Nuaimi, 2019). The invasion by a US led coalition in March 2003 overthrew the government of Saddam Hussein and temporarily replaced it with a Coalition Provisional Authority that was slow to address healthcare needs and struggled to provide security (Medact, 2008). The Iraq War officially ended in 2011 (Britannica, 2022), however it was not until 2018 that the humanitarian logistics cluster commenced the closure of their operation with the Logistics Cluster deactivation scheduled between 2019-2020 (Logistics Cluster Iraq, 2019). Iraqi civilians have borne the consequences of war and violence over the last decades suffering adverse effects on their health, wellbeing, basic needs, and years of life lost (Lafta and Al-Nuaimi, 2019).

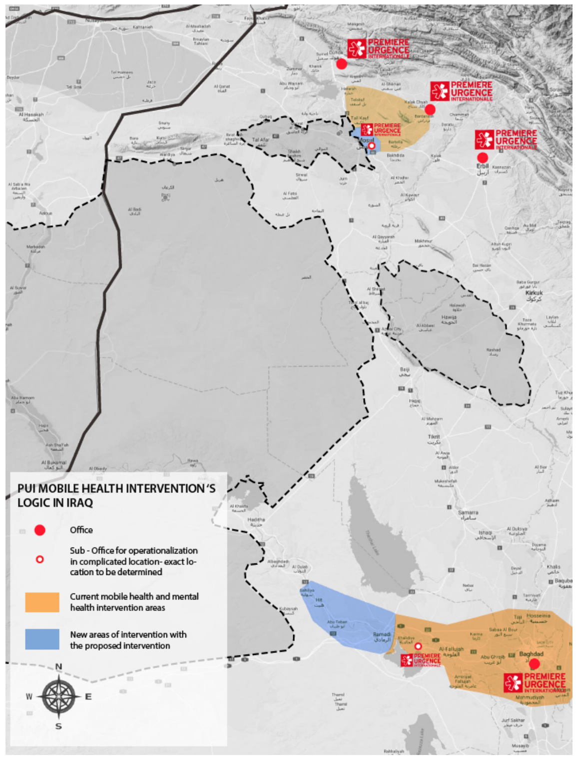


Figure 1.6: PUI Deployments in in Iraq (PUI, 2017d)

From 2014 to 2018 PUI deployed mobile clinics in the regions of Mosul, Erbil, Duhok, Baghdad, Al-Fallujah, and their population settlements as depicted in Figure 1.6. These mobile clinic deployments were intended to serve citizens that otherwise would not have easy access to healthcare in their regions and served as a temporary solution for those with chronic diseases and in need of medical services (Iraq Health Cluster, 2014). A representative from each NGO deploying mobile clinics in Iraq would attend the monthly health cluster meeting, along with the MoH's and WHO's representatives, where regions identified by the MoH would be assigned to NGO's partners according to the services provided (PUI, 2017f). In the case of PUI, they offered the following services with every mobile clinic deployments in Iraq: patient triage (i.e., vital signs assessments), general primary healthcare consultations for uncomplicated acute conditions and acute conditions in children, oral rehydration solutions, screening for chronic non communicable diseases for diabetes and hypertension, treatment of chronic diseases, stabilization and immediate referral for secondary care for emergency cases, nutrition for children 6 to 59 months and pregnant lactating women, health education, assessment of immunization status of all children and pregnant women, and reproductive health (PUI, 2017c). Also, some mobile clinics were equipped to provide mental health services, testing, and dispense medications as prescribed by the medical staff (PUI, 2017c).

During the deployments PUI had between four and five mobile clinics (PUI, 2016a). In addition, PUI oversaw the operation of two primary healthcare facilities and several offices and sub offices from where clinics could depart from (PUI, 2016a). These clinics consisted of a pickup truck and a subcontracted driver that served as a security personnel, medical personnel, and the required medical and set up equipment (PUI, 2017f,e). The mobile clinics would often be installed in abandoned residencies, communal spaces, or the residence of the contact person (PUI, 2017f). Clinics were set up with the use of folding tables, chairs, tents, and dividers. This means that deployments by PUI in Iraq required set up and clean up times for every location visited.

The human resources required deploy PUI's mobile clinics in Iraq varied based on the type of clinic (i.e., primary health or primary health and mental health). To oversee the deployment each office or departure point had a deputy project manager and a health officer. The deputy project manager was responsible of ensuring the effective, safe and timely implementation of mobile primary healthcare activities (PUI, 2017a). The health officer was in charge of ensuring standards were respected in all deployments as well as coordinating with health, civil, and security actors on the field (PUI, 2017b). All mobile clinics had a nurse, a doctor, a pharmacist, and a health assistant (PUI, 2017f). When the mobile clinic provided mental health services it would have in addition a team leader, psychosocial worker, and a psychologist (PUI, 2017e).

For their deployments PUI designed a weekly schedule for the mobile clinics, in which based on the number of available clinics and the vulnerability they would select locations that can be visited and in an equitable way distribute the load between the available clinics (PUI, 2017f). They also had to comply with the standards established by the MoH such as the maximum number of patients each clinic could serve (Iraq Health Cluster, 2014). PUI deployed mobile clinics in conflict zones and post-conflict zones. A location is considered a conflict zone if it is located eight kilometers from the front lines, has been affected by a security incident within the previous three days, or presents difficult access due to insecurity or checkpoint restrictions (PUI, 2017j), whereas post-conflict zones do not adhere to these criteria. Despite clinic healthcare service operations similarities in both contexts there were additional security protocols for the personnel when it is deployed to a conflict zone.

1.5.2 Specificities of Deployments in Conflict Zones

To ensure the safety of personnel and people seeking healthcare PUI had in place a standard operating procedure based on guidelines establish by the MoH (Iraq Health Cluster, 2014). When clinics were to be deployed to a conflict zone the project manager and health officer must ensure that appropriate documentation is obtained to pass security checkpoints, constant monitoring is maintained on the security situation, as well guarantee that the driver assigned had an appropriate knowledge of the roads and locations (PUI, 2017j). Either the project manager or the health officer must make contact with their contact at the location 24 hours prior to the visit, to confirm the zone is still secure for health delivery (PUI, 2017j). The day of the scheduled visit teams deployed to conflict zones had to report earlier to the departure point and depart at earlier times than teams deployed to post-conflict zones (PUI, 2017d). Through their deployment they had to maintain constant communication, i.e., security checks at departure, checkpoint arrival, location arrival, every 60 minutes while providing services, when leaving the location, at return to checkpoint, and return to base (PUI, 2017j). When arriving to a security checkpoint, it is possible that access is denied and the team has to return to the departure point

(PUI, 2017d,j) but when possible the team could be reassigned to a different location for that day. This change of plan ran the risk of low demand due to an unplanned visit (PUI, 2017f). The health officer and the project manager highlighted the fact that the main challenges faced during the deployment to a conflict zone was related to the change in security status without warning, that the information regarding the needs at the location can be misleading (i.e., needs might have been underestimated), and that the locations for set up might be contaminated (e.g., mines bombs) (PUI, 2017e). Although, post-conflict zones do not present the same security threats during deployments they still presented an uncertainty in the demand and access to the location from where services would be provided. Hence, deploying mobile clinics in conflict zones requires more time invested in security verification and it also comes with the added uncertainty of not knowing that the location can be serviced.

The resources assigned to a mobile clinic must tend to administrative tasks, which takes time away from healthcare services. Teams deployed to post-conflict zones still had to report at the departure point before and after their deployment (PUI, 2017f). Once they arrived at the location where services would be provided they must set up prior to providing services and clean up after at every location (PUI, 2017g,d). The needs at post-conflict location could also be misleading as internally displaced people may be returning to their previous homes (PUI, 2017e). Also, if an abandoned residence was selected as the point of service and the family members returned to the location the clinic would be relocated to another public location or an occupied residence (PUI, 2017e). Additionally, pharmacists had to do an inventory before and after a deployment (PUI, 2017h). The medical doctor and psychologist were responsible to provide an after action report when returning to the departure point (PUI, 2017g,i). These reports were used to report incidents (i.e., injury and mortality) to the MoH and health cluster (PUI, 2016a).

Based on the insights gained from PUI's operations in Iraq we can conclude that deployments of mobile clinics in conflict and post-conflict zones require additional time from resources. Also, both conflict and post-conflict zones add an extra uncertainty in demand, availability of set up location, fund availability, and access. Additionally, the availability of funds is out of the hands of practitioners as this is supplied by donors and sponsorship (PUI, 2016a, 2017f). This presents a hurdle when deploying mobile clinics in any context, as practitioners need to correctly manage the funds available to maximize the impact of their deployment. These complications demonstrate that when planning a mobile clinic deployment in a zone affected by conflict practitioners must thoroughly design and evaluate their plan to ensure it is robust (i.e., alternate set up location and a replacement location).

1.6 Research Gaps

The WHO and its partners often resort to mobile clinics to provide healthcare services to isolated and vulnerable groups during crisis responses, including conflicts (WHO, 2016a). Despite the numerous benefits and endorsements of mobile clinics deployments for humanitarian healthcare, their usage involves several logistics challenges (e.g., limited resources and security issues) and they are costly to operate (ICRC, 2006). Not to mention the additional complications added when providing humanitarian healthcare in conflict zones (Department of vaccines and biologicals, 2000) that enhance the "logistical nightmare"of mobile clinic deployments (Du Mortier and Coninx, 2007a). This motivates the need for the development of decision support tools to facilitate the deployment and management of mobile clinics by humanitarian field practitioners in conflict and post-conflict zones. In this section we identify and suggest empirical and support tools studies that can prove useful for mobile clinic deployments in conflict and post-conflict zones. It aims to answer RQ3 and provide related practical insights.

Empirical Studies and practical guidelines

Due to the scarce academic literature that studies mobile clinic deployments in conflict zones, authors should further document them. Empirical studies should aim to shine a light on the best practices and suggest directions for standardization of deployments of mobile clinics in complex emergencies such as conflict zones. Even though the situations present in conflict zones can be unpredictable and may require adjusting plans as the relief is delivered, as shown in Section 1.3 and in Figure 1.5, standard guidelines to aid in the three planning phases (i.e., strategic, tactical, and operational) can result in a more effective deployment. Also, such studies should analyze further the differences between conflict and post-conflict zones to justify practices and services offered. Moreover, a study that documents the demands for specific services provided by mobile clinics can aid practitioners at the time of selecting the services offered and the resources allocated. We show in Section 1.3 that information on the healthcare needs of the populations affected by conflicts is not easily accessible. Therefore, studies that document or propose guidelines to estimate the demands before a humanitarian relief delivery would allow practitioners to meet the needs of those affected with better accuracy. As pointed out by Du Mortier and Coninx (2007a) there are studies documenting healthcare operations of mobile clinics, but the logistic element is lacking in the literature, especially in conflict and post-conflict zones. Studies should focus on developing and proposing the use of frameworks that are easy to use and implement by practitioners and that would serve both to plan deployments at a strategic, tactical, and operational level as well as to justify the resources needed. Finally, once there are more studies and insights derived from the academic literature researchers can strive to consolidate knowledge and provide a complete framework for mobile clinic deployments in conflict and post-conflict zones.

Strategic Decision Support Tools

The strategic decisions practitioners are forced to make, after the deployment of mobile clinics are identified as a viable and the only solution (Du Mortier and Coninx, 2007a; ICRC, 2006), is the appropriate number of mobile clinics, healthcare practitioners, and medical equipment, as well as the available budget (Du Mortier and Coninx, 2007a). As pointed out by Leseure et al. (2010) "unfortunately, in a world of scarce resources, although humanitarian action has no price, it obviously has a cost, and an improved management of this cost has an influence on the ability to send relief [...]"(p .337). Therefore, tools that concentrate on maximizing the outreach or potential for humanitarian healthcare relief based on limited budgets will prove useful for practitioners, specially in conflict zones where there is a limited availability of resources (Garfinkel and Skaperdas, 2007). Such tools can be developed in the form of a mathematical model, a simulator, or even a cost-effectiveness analysis framework to support budget allocation. Not only will these tools be useful in the strategic decision process but also when elaborating the proposals or annual reports to sponsors as the organization will be able to justify the needs for specific quantities based on a scientific method and concrete evidence.

Moreover, the allocation of the available budget results in constraints for the number of mobile clinics, healthcare practitioners, and medical equipment. Although, the mobile clinics (i.e., vehicles) and medical equipment can be inkind donations and healthcare practitioners can be volunteers there will still be a cost associated to the maintenance and per diem that will constrain the available resources. Practitioners can benefit from a tool to evaluate different scenarios of varying resources in the deployment. Said tools could take the form of simulators with which decision makers can make educated decisions and correctly plan the number of resources that can be maintained throughout the deployment based on the organizations goals and status of the conflict. Additionally, by measuring the effectiveness of healthcare resources, such as mobile clinics, healthcare practitioners, and medical equipment, it will result in a transparent and consistent decision making (Eichler et al., 2004).

The remaining decision at the strategical level would be the selection of locations that will receive healthcare services by the mobile clinics. Based on the capacity of the deployment dictated by the resource allocation practitioners may be forced to select a subset of the locations that are in need of healthcare. At this phase, optimization models can aid practitioners to identify the set of locations that can offer access to within a one hour walk for at least 80% of the affected population in order to comply with humanitarian standards (Sphere Association, 2018). Coverage maximization problems, facility location problems, among others can be adapted to support the location decision of mobile clinic deployments while considering the healthcare needs and the vulnerability of the population. A detailed framework or assessment tool for location selection based on the community needs and available resources is another alternative.

Tactical Decision Support Tools

At the tactical phase, practitioners are bounded by the strategical decisions made a priori. Decision makers must schedule the mobile clinics, and also decide on the frequency of visits, the days, and the time of day to deploy the mobile clinics to each location (Du Mortier and Coninx, 2007a; ICRC, 2006). Practitioners must take into account the frequency with which the same communities can be visited as this will determine whether the mobile clinic should offer care or referral for acute illnesses (McGowan et al., 2020). McGowan et al. (2020) underscores that infrequent or unpredictable visits can discourage communities from seeking early care, and by consequence worsen acute illness outcomes. Efforts have already been directed towards decision support tools to determine the frequency of visits offered by mobile clinic deployments (De Vries et al., 2021b,a). This tool however does not consider the additional complexity conflict and post-conflict zones pose. Further consideration must be given to the uncertainty during conflicts and the dangers of medical personnel being targeted (Gordon et al., 2010; Guha-Sapir and van Panhuis, 2002; Gates et al., 2010; Zwi and Ugalde, 1989; Levy, 2002). Scheduling and routing decision support tools for mobile clinics have also been addressed in the literature (Hodgson et al., 1998; Doerner et al., 2007; Santa González et al., 2020). But the uncertainty or security risks faced in a conflict zone when transporting mobile clinics and medical personnel (Rubenstein and Bittle, 2010) and the fact that civilians seeking healthcare are targeted (Hovil and Werker, 2005) have not been addressed. Even thought the WHO has provided a guide for medical interventions with mobile clinics in conflict zones (WHO, 2021), there is no decision support tool or framework that considers the risks of transporting medical equipment and personnel in insecure areas.

Operational Decision Support Tools

At the operational level practitioners must implement their plans and afterwards they must also evaluate the outcome, producing after action reports (McGowan et al., 2020; ICRC, 2006). There is a dearth of standardize guides to explicitly guide the implementation of mobile clinic deployments. Hence, practitioners can benefit from more literature that seeks to detail and standardized procedures (Leibowitz et al., 2021). More empirical research, such as case studies, longitudinal studies, or delphi analyses, can provide more understanding and seek to standardize practices or highlight the directions towards standardization. Moreover, McGowan et al. (2020) highlights the need to develop standard indicators for evaluating the use of mobile clinics in conflict zones and complex emergencies. Therefore, researchers can contribute by developing a framework for practitioners to standardize the performance indicators and metrics during mobile clinic deployments in conflict and post-conflict zones.

Although the decision support tools suggested in this study have been broken down by decision level (i.e., strategical, tactical, and operational), authors can still strive to develop decision support tools that address all three levels. Ideally a framework that encompasses all levels would provide practitioners all the required support. However, developing a one size fits all for conflict and post-conflict that consolidates all three decision levels can be an arduous task and might require more literature.

1.7 Conclusions

There is a dearth of literature documenting mobile clinic deployments (McGowan et al., 2020) and practitioners material to support mobile clinic deployments (Du Mortier and Coninx, 2007a; ICRC, 2006). Despite various humanitarian organizations created to ease the suffering of the victims of conflict (Rysaback-Smith, 2015), researchers have ignored the contexts of conflict zones (Altay et al., 2021). This study illustrates the operations entailed by mobile clinic deployments in conflict zones and post-conflict zones. It also highlights logistical difficulties arising both during and after conflicts for practitioners deploying mobile clinics. Mobile clinic deployments in conflict zones are faced with the same logistical challenges and decisions as those deployed in areas where conflict and violence are not present (Du Mortier and Coninx, 2007a). However, deployments in conflict zones are faced with additional security risks, economical constraints, and uncertainty (Gordon et al., 2010; Guha-Sapir and van Panhuis, 2002; Gates et al., 2010; Zwi and Ugalde, 1989; Levy, 2002; Garfinkel and Skaperdas, 2007).

The literature on mobile clinic deployments in conflict zones is lacking documentation and development of decision support tools to aid practitioners. This paper can serve as a road map for researchers that want to contribute to the literature on mobile clinic deployment in conflict zones. Studies should further document mobile clinic deployments in conflict and post-conflict zones, as well as develop decision support tools for practitioners. At the strategical, tactical, and operational decision levels there is a need for tools to identify feasible solutions and a framework to evaluate the performance of different alternatives. Further developing tools to evaluate performances will not only contribute to a more efficient delivery of healthcare but it will also aid practitioners in justifying strategical decisions. Once there are more studies and insights derived from the academic literature researchers can strive to consolidate different tools and provide a complete framework for mobile clinic deployments in conflict and post-conflict zones.

Chapter 2

Mobile clinics deployment for humanitarian relief: A multi-period location routing problem

2.1 Introduction

Humanitarian crises induce challenges for health service access and delivery, including disrupted health 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 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, members of the United Nations (UN) pledged to "ensure healthy lives and promote well-being for all at all ages" (UN, 2015a), but despite the progress made to improve health worldwide, the rate of improvement has slowed down, 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), such as communities affected by a disaster, conflict and post-conflict zones, refugee camps, and remote and rural areas (Cherkesly et al., 2019). 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 (Du Mortier and Coninx, 2007a; Blackwell and Bosse, 2007; Gibson et al., 2011; Fox-Rushby and Foord, 1996).

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 (McGowan et al., 2020; Du Mortier and Coninx, 2007a). 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 several healthcare 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 (WHO, 2016a), 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 (The New York Times, 2021; CBCnews, 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.

2.1.1 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 (Première Urgence Internationale, 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. For example, in the case of PUI, the organization opted for deploying five mobile clinics in a specific district of Iraq, with the applicable equipment and staff, as a mode to provide ambulatory primary healthcare services. The organization revisits these decisions every year depending on the situation. 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. This would not be possible without an efficient tool such as the one proposed in this paper.

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 customers to serve (locations to visit and the number of people to serve in this case) have to be selected. Note that in this case, the notion of profits is accounted for by considering healthcare benefits. The multiple-period representation allows us to capture the fact that the time and frequency of visits can encourage or discourage patients from seeking healthcare (McGowan et al., 2020). This also allows to capture the notion of continuity of care when accounting for the benefits of serving patients several times. The benefit-collection representation allows us to capture the fact that the patients to visit have to be chosen because all of the population cannot be covered due to limited resources. In our MLRP with benefits, we consider a homogeneous fleet of mobile clinics, as the mobile clinic equipment and the assigned teams of medical staff are the same (Du Mortier and Coninx, 2007a). Multiple origin and destination depots are also considered because humanitarian crises often affect people over widespread areas. The optimization model 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 us 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).

2.1.2 Contributions and organization of this paper

Traditionally, MLRP formulations minimize the routing costs as well as the costs of opening depots over a planning horizon. However, in humanitarian operations, while costs are important, the primary goal is to maximize the relief provided to vulnerable populations (Leseure et al., 2010). 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 benefits (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. In the formulation and estimation of the healthcare benefits, *coverage* (also known as physical accessibility) is interpreted as “the availability of good health services within reach of those who need them" (WHO, 2014), whereas *continuity* of care is defined as “the degree to which a series of discrete healthcare events is experienced by people as coherent and interconnected over time and consistent with their health needs" (WHO, 2018). Our model also allows us to conduct sensitivity analyses on the modeling of the benefits as well as the effect of strategic decisions and tactical routing policies to derive valuable managerial insights. For example, the benefits of increasing the number of mobile clinics (a strategic decision in this context) and the number of people visited per village within a route (a tactical decision) will be evaluated.

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 ICRC, 2006; Du Mortier and Coninx, 2007a). 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 Kunz et al. (2017) and Gupta et al. (2019). Therefore, we use data collected on the field by PUI, which comprises healthcare and demographics information of vulnerable populations. Accessing, processing, and analyzing data represents a contribution of our work. Still, our approach is sufficiently general to support any mobile clinic deployment even if our model has been tested on real data of humanitarian operations in Iraq.

The remainder of this paper is organized as follows. A literature review is presented in Section 3.2. Section 2.3 presents the problem definition and the proposed mathematical model. In Section 2.4, computational results and managerial insights are discussed. Finally, conclusions are derived in Section 3.6.

2.2 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 (Jabbour et al., 2017). In this section, we position our contributions in the literature. First, we discuss previous studies that propose mathematical models to tackle mobile clinic deployments. 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.

2.2.1 Mobile clinics for non humanitarian relief

Through the literature, authors have documented several healthcare services that can be provided by mobile clinic deployments. Mobile clinics 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 (Murphy et al., 2000; Dawkins et al., 2013), sexually transmitted diseases (Ellen et al., 2003). Also, mobile clinic deployments have been deployed to offer family planning and women's reproductive healthcare services (Phillips et al., 2017; Jamir et al., 2013; Al-Attar et al., 2017). Deployments of mobile clinics have also been used to provide mental health services for refugees (Samakouri et al., 2022; Peritogiannis et al., 2022; Robinson and Segrott, 2002), underprivileged people (Collinson and Ward, 2010), and for addicts (Jamir et al., 2013). Authors have proved that mobile clinics are an effective source of continuity of care for people with mental illness and can improve their functioning in their community. 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 mobile clinic deployments, independent of the service offered. Even though the model is illustrated with a humanitarian relief effort in a conflict zone, it can be adapted to other contexts such as those studied in the literature.

2.2.2 OR/MS approaches to mobile clinics

To the best of our knowledge, two studies have proposed OR/MS approaches for mobile clinic deployment for humanitarian relief. 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) aims 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.

To provide mobile health services in rural areas, Savaşer (2017) have proposed 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.

Our study is the first to propose a location-routing approach to plan mobile clinic deployments over multiple periods. Furthermore, we propose a profit (i.e., benefit) maximization objective making this study the first to consider continuity and coverage benefits in mobile clinic deployment planning.

2.2.3 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 (Martin et al., 2002; Agyemang-Duah et al., 2019), 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 Naji-Azimi et al. (2012), Burkart et al. (2017), 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 (Nickel et al., 2012; Milburn and Spicer, 2013; Bowers et al., 2015). Carello and Lanzarone (2014) also suggest three types of patients (requiring hard, partial, or no continuity of care) and minimize the cost associated with reassignments of healthcare practitioners. Wirnitzer et al. (2016) propose different objectives 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, and thus continuity of care, whereas Cinar et al. (2019) maximize the prize collected per patient per visit. Mosquera et al. (2019) argue that continuity of care may be impossible to satisfy and, hence, impose a soft constraint on the number of visits by a healthcare practitioner to a specific patient. Grenouilleau et al. (2020) also include the time and day as part of 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 2.4.3 and 2.4.4). 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.

2.2.4 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). Because we aim to maximize the benefits, which are evaluated with a function that combines coverage and continuity of care, offered to beneficiaries with mobile clinics services operating with limited resources (i.e., number of mobile clinics and budget), 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). This healthcare benefit is therefore associated with covering villages and serving patients according to their vulnerability evaluated by experts. 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. (2005b), and Vansteenwegen et al. (2011b).

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., 2011b). 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, where the notion of profit is a benefit measured with a function modeling the value of the coverage and continuity of care, see Section 2.4.3 for more details, which reflects the vulnerability of the locations.

2.2.5 Location-routing problem

The LRP is within the field of location analysis and 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 Prodhon and Prins (2014) and Drexl and Schneider (2015). The LRP decisions include the number, size, and location of the depots, the allocation of demand points to depots, and the routing of vehicles (Lopes et al., 2013). Moreover, depots and vehicles can be capacitated or uncapacitated. In general, the literature related to the LRP has focused on minimizing costs (i.e., fixed cost, depot selection cost, and route selection) (Prodhon and Prins, 2014). To solve the LRP, many exact algorithms have been proposed such as branch-and-price (Berger et al., 2007) and branch-and-cut algorithms (Belenguer et al., 2011). Tighter solution bounds are derived by Contardo et al. (2013a) and Contardo et al. (2013b) while using exact separation procedures and column generation.

Location-routing problems in the context of humanitarian relief

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

To the best of our knowledge, only a few studies combine location and routing decisions for humanitarian relief. Yi and Özdamar (2007) propose 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. Balcik (2017) proposes to model the selection of sites for evaluations of post-disaster conditions as a variant of the LRP, known as the selective assessment routing problem. In this problem, a subset of sites must be selected to conduct a needs assessment and vehicles are used to visit these sites. Cherkesly et al. (2019) propose a location-routing approach for the network design of community health workers in underserved areas, where the recruitment of community health workers and supervisors are taken as location decisions, while the training of community health workers by supervisors is modeled as routing decisions. In addition, a maximum coverage radius is imposed on community health workers. More recently, Arslan et al. (2021) propose a location-routing approach for the placement of refugee camps and the delivery of public services to refugee camps in Turkey, where refugee camps must be located and public services must be delivered to camps. 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.

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, 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 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.

The literature on the MLRP is scarce and is mainly of methodological or academic nature (Drexl and Schneider, 2015). Nagy and Salhi (2007) underscore that only one fifth of the LRP literature is application oriented and Prodhon and Prins (2014) call for further developments and more realistic MLRPs. With this study we contribute to the location-routing literature and the mobile clinic deployment literature. 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. Our study is one of the few studies that link theoretical knowledge with a real world application. 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. This data is used to formulate and test the model, but the proposed model is generalizable and can be adapted to other contexts where mobile clinics are deployed. Moreover, impacts of coverage and continuity of care as well as routing policies are analyzed.

2.3 Problem definition and mathematical formulation

In this section, we first explain the MLRP for the context of mobile clinics in an underserved area. Then, we present the notation and formulate the problem with a set-packing formulation. A summary of the proposed mathematical notation is presented in Appendix 3.6.

2.3.1 The MLRP for mobile clinics deployment

When using mobile clinics to alleviate the deficit of healthcare during humanitarian crises, due to the 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. To do so, the results of the needs assessment will allow to determine representative values of the benefits based on the vulnerability of the targeted villages. The objective consists of maximizing the total benefits which include the coverage (COV) and continuity of care (CNT) benefits. The decisions must respect the budget constraints (i.e., costs to open depots, costs to cover villages, and routing costs), the capacity constraints (i.e., maximal number of patients and duration per mobile clinic), and the resting periods between visits.

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) which is homogeneous for all villages, but our model allows to have heterogeneous values. The number of visits (treatments) each patient receives in a covered village is associated with a continuity benefit (CNT benefit) which is heterogeneous according to the characteristics of the villages (e.g., vulnerability). 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. The CNT marginal benefit can remain constant when the number of visits to a patient increases or it can decrease (see sections 2.4.3 and 2.4.4). 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.

2.3.2 Notation and mathematical model

The MLRP for mobile clinics deployment is defined on a graph $\mathscr{G} = (\mathscr{N}^e \cup \mathscr{N}^c, \mathscr{A})$, where $\mathscr{N}^e$ is the set of nodes representing the potential depots, $\mathscr{N}^c$ is the set of nodes representing the villages to cover, and $\mathscr{A}$ is the arc set. Each village $i \in \mathscr{N}^c$ is associated with a population $p_i \geq 0$. The fixed cost of operating a depot $i \in \mathscr{N}^e$ is given by c_e, and the fixed cost of covering a village $i \in \mathscr{N}^c$ is given by c_c. Let $\mathscr{V} = \{1, ..., |\mathscr{V}|\}$ be the set of visit frequencies, i.e., the number of times a patient may be served in a village, where $|\mathscr{V}|$ 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 $i \in \mathscr{N}^c$, and of a CNT benefit β_i^v associated with serving a patient $v \in \mathscr{V}$ times at village i. More details on the calibration of these parameters are provided in Section

2.4.3 and 2.4.4 for β_i and in sections 2.4.4 for β_i^v. The arc set represents the shortest paths between two nodes and is defined as $\mathscr{A} = \{(i,j) : \{i,j \in \mathscr{N}^e \cup \mathscr{N}^c\}\}$, where each arc $(i,j) \in \mathscr{A}$ 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 $\mathscr{T}$ 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 $\mathscr{R}$ be the set of feasible routes, with $\mathscr{R} = \cup_{t\in\mathscr{T}}\mathscr{R}^t$, where $\mathscr{R}^t$ is the set of feasible routes at time period $t \in \mathscr{T}$. Each route $r \in \mathscr{R}$ is defined by an ordered vector of vertices $(i_1, i_2, ..., i_{n-1}, i_n)$, $i_k \in \mathscr{N}^e \cup \mathscr{N}^c, k = 1, \ldots, n$. Routes start and end at a depot, i.e., $i_1, i_n \in \mathscr{N}^e$, and serve patients in a subset of villages $\{i_2, \ldots, i_{n-1}\} \in \mathscr{N}^c$. 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 2.4.3 and 2.4.4). Each route $r \in \mathscr{R}$ is defined by a binary vector $\mathbf{a}$, where $a_{ir} = 1$, if route $r \in \mathscr{R}$ visits node $i \in \mathscr{N}^e \cup \mathscr{N}^c$, and zero otherwise. Each route is characterized by a total activity time, which includes the travel time, the setup time at each village θ, and the patient service time in each village (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 Appendix **??**.

The MLRP is formulated as a set-packing formulation that seeks to maximize the total benefits under a budget and several routing constraints. To formulate the problem, we use binary variables x_i equal to one if village $i \in \mathscr{N}^c$ is covered (selected), y_i equal to one if depot $i \in \mathscr{N}^e$ is selected, λ_r^t equal to one if route $r \in \mathscr{R}^t, \forall t \in \mathscr{T}$, is selected, and ω_i^v equal to one if all the population at location $i \in \mathscr{N}^c$ 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.

$$\text{Maximize} \sum_{i \in \mathcal{N}^c} \beta_i x_i + \sum_{i \in \mathcal{N}^c} \sum_{v \in \mathcal{V}} \beta_i^v \pi_i^v \tag{2.1}$$

$$\text{s.t.} \quad \sum_{i \in \mathcal{N}^e} c_e y_i + \sum_{i \in \mathcal{N}^c} c_c x_i + \sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{R}^t} c_r \lambda_r^t \leq B \tag{2.2}$$

$$\sum_{r \in \mathcal{R}^t} \lambda_r^t \leq m \quad \forall t \in \mathcal{T}, \tag{2.3}$$

$$a_{ir} \lambda_r^t \leq y_i \quad \forall i \in \mathcal{N}^e, \quad t \in \mathcal{T}, \quad r \in \mathcal{R}^t, \tag{2.4}$$

$$\sum_{r \in \mathcal{R}^t} a_{ir} \lambda_r^t = \sum_{r \in \mathcal{R}^{t+1}} a_{ir} \lambda_r^{t+1} \quad \forall i \in \mathcal{N}^e, \quad t \in \mathcal{T}, \tag{2.5}$$

$$\pi_i^v \leq x_i \quad \forall i \in \mathcal{N}^c, \quad v = 1, \tag{2.6}$$

$$\sum_{r \in \mathcal{R}^t} a_{ir} \lambda_r^t + \sum_{t'=t+1}^{t' \leq t+\eta} \sum_{r \in \mathcal{R}^{t'}} a_{ir} \lambda_r^{t+1} \leq 1 \quad \forall i \in \mathcal{N}^c, \quad t \in \mathcal{T}, \quad t \leq |\mathcal{T}| - 1, \tag{2.7}$$

$$\frac{\sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{R}^t} G_{ir} \lambda_r^t}{p_i} \geq \sum_{v \in \mathcal{V}} \pi_i^v \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}, \tag{2.8}$$

$$\pi_i^v \geq \omega_i^v \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}, \tag{2.9}$$

$$\omega_i^v \geq \pi_i^{v+1} \quad \forall i \in \mathcal{N}^c, \quad v \leq |\mathcal{V}| - 1, \tag{2.10}$$

$$x_i \in \{0,1\} \quad \forall i \in \mathcal{N}^c, \tag{2.11}$$

$$\pi_i^v \geq 0 \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}, \tag{2.12}$$

$$\pi_i^v \leq 1 \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}, \tag{2.13}$$

$$y_i \in \{0,1\} \quad \forall i \in \mathcal{N}^e, \tag{2.14}$$

$$\lambda_r^t \in \{0,1\} \quad \forall r \in \mathcal{R}^t, \quad t \in \mathcal{T}, \tag{2.15}$$

$$\omega_i^v \in \{0,1\} \quad \forall i \in \mathcal{N}^c, \quad v \in \mathcal{V}. \tag{2.16}$$

The objective function (2.1) maximizes the total benefit computed as the sum of the COV and CNT benefits. We explain how benefits have been modeled according to the population vulnerability assessment in Section 2.4.3. Constraint (2.2) 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 (2.3) ensure that no more than the maximal number of mobile clinics available are used for the deployment. Constraints (2.4) 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 (2.5) 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 (2.6) 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 (2.7) 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 (2.8) link the route variables with the percentage of the population served v times. Constraints (2.9) and (2.10) 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 (2.11)–(2.16) define the variable domain.

2.4 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 2.4.1, and Section 2.4.2 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 2.4.3. The results of the sensitivity analyses are presented in Section 2.4.4.

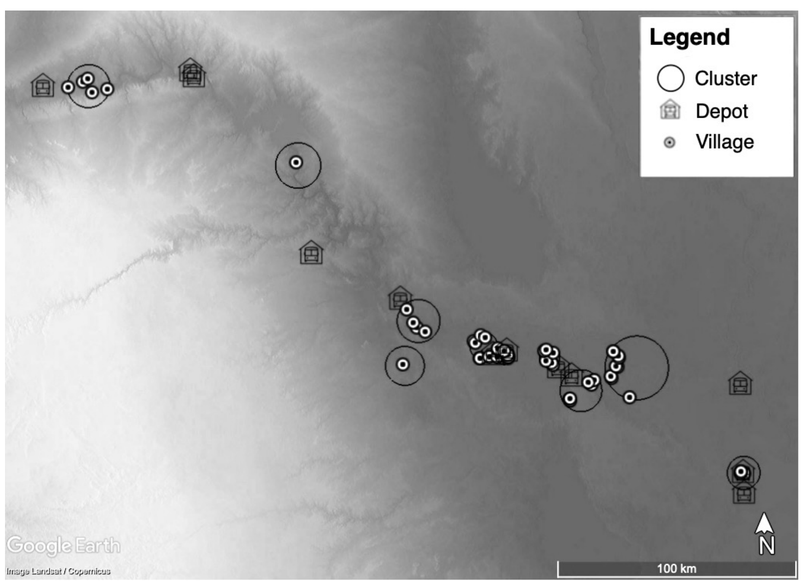


Figure 2.1: Location of Potential Depots and the Villages to Cover

2.4.1 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 2.1). In Figure 2.1, we can notice that the network is relatively sparse with some clustered villages along few roads. This is common in the context of humanitarian aid and development programs, often deployed in underserved or remote areas (e.g., Cherkesly et al., 2019; Rancourt et al., 2015; VonAchen et al., 2016). 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 $d_{ij}, \forall (i,j) \in \mathscr{A}$ 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 2.1. The area that PUI aims to cover is vast as the maximum distance between any two villages is around 414 km. However, in Figure 2.1 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 2.1: Distance Between Villages and Depots in Km

Distance between	Min	Max	Average	St. dev.
Villages ($d_{ij}, \forall i, j \in \mathscr{N}^c$)	0.0	402.5	98.9	90.9
Potential depots and villages ($d_{ij}, \forall i \in \mathscr{N}^e, j \in \mathscr{N}^c$)	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 $s_i, \forall i \in \mathcal{N}^c$. Table 2.2 presents the aggregated characteristics of the villages. We report minimal, maximal, average, standard deviation, and coefficient of variation (CoV) values for the population, as well as the health score computed by our partner. Due to confidentiality and security reasons, we can only report aggregated values and cannot report detailed information pertaining to the specific needs assessment data. These characteristics show that the villages are heterogeneous in terms of size (i.e., population), but that their health scores are more similar. The data does not show a trend between the size and the health score of the villages.

Table 2.2: Characteristics of the Villages

	Min	Max	Average	St. dev.	CoV
Population (p_i)	70	28,000	1,640	4,080	2.49
Health score	174	370	295	33	0.11

2.4.2 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 2.3. 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 2.3: 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

2.4.3 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 2.4.4) 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.

Parameters of the *base case*

In terms of operations, a two-week (ten days, $|\mathscr{T}| = 10$) 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. The service time may vary for each patient, but such data has not been collected by our partner. Our partner, therefore, uses an average service time for each patient of five minutes ($\gamma = 5$) to plan and evaluate their program. In practice, when scheduling mobile clinics and using an average of five minutes, allows one to properly represent the total time spent at a village during a visit. 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 ($|\mathscr{V}|$). 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:

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

The performance of the *base case* is presented in the following section, whereas the impacts of modifying this *base case* are presented in Section 2.4.4 to evaluate potential improvements of the current solution.

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 2.4 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 2.2) and each depot is used exactly ten times.

Table 2.4: Results Obtained for the *Base Case*

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

2.4.4 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

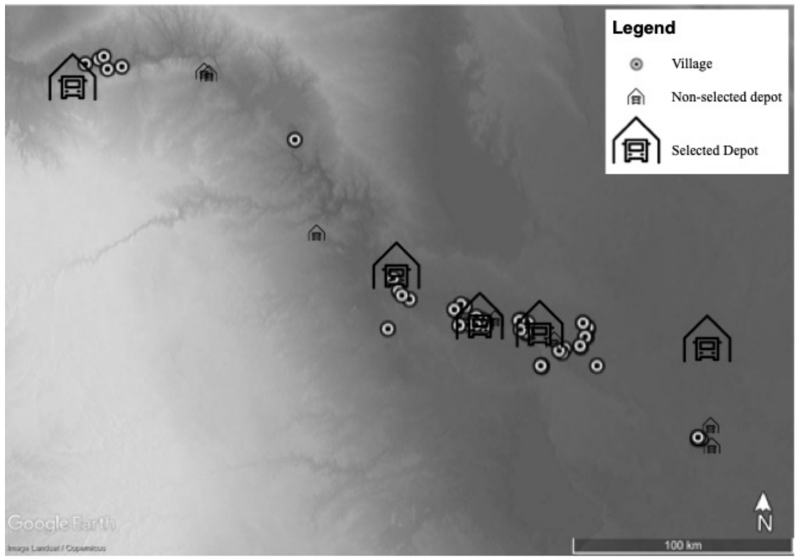


Figure 2.2: Selected Depots for the *Base Case*

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 3.6.

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 evaluate how some tactical decisions and policies impact healthcare and logistics performance. We start by analyzing how the marginal CNT benefit function impacts the performance indicators. Then, we study the computation of the number of visits to each village in a route to understand its impacts on the solutions. Finally, we analyze the effect of the choice of the origin and destination depots. For these analyses, 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.

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.

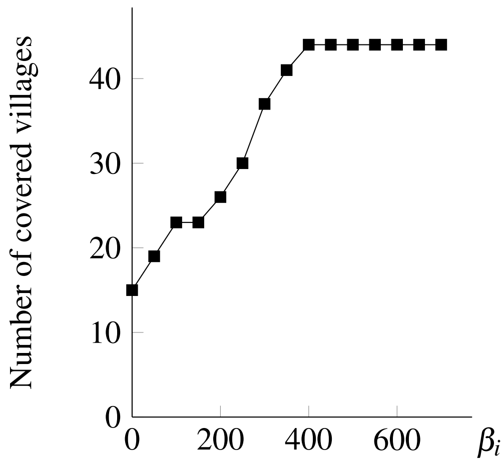


Figure 2.3: Number of Covered Villages

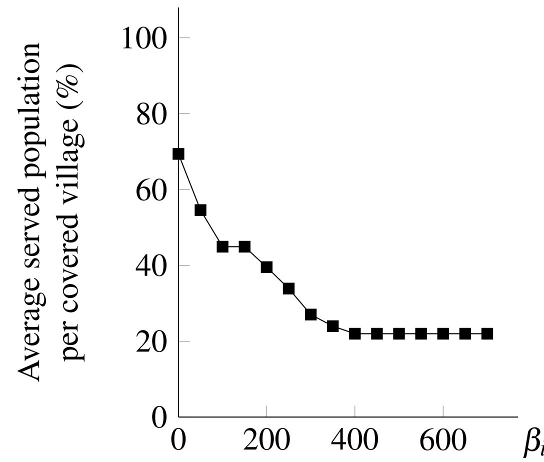


Figure 2.4: Average Proportion of the Population Served at Least **Once**

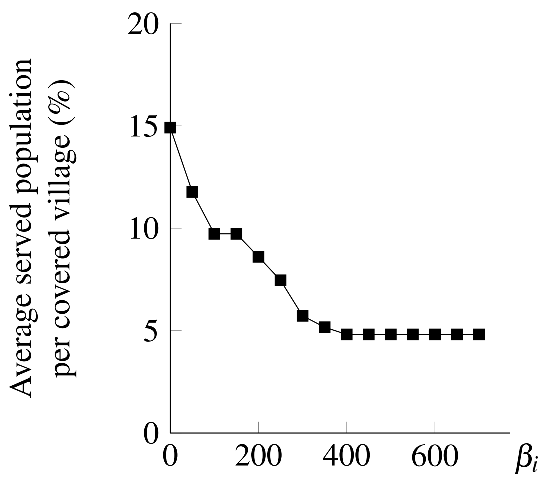


Figure 2.5: Average Proportion of the Population Served at Least **Twice**

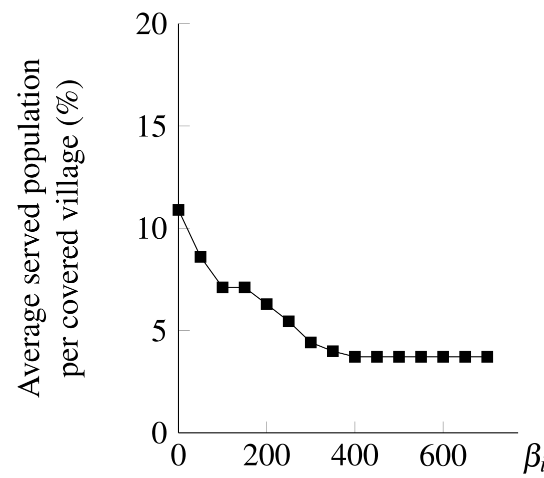


Figure 2.6: Average Proportion of the Population Served at Least **Thrice**

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

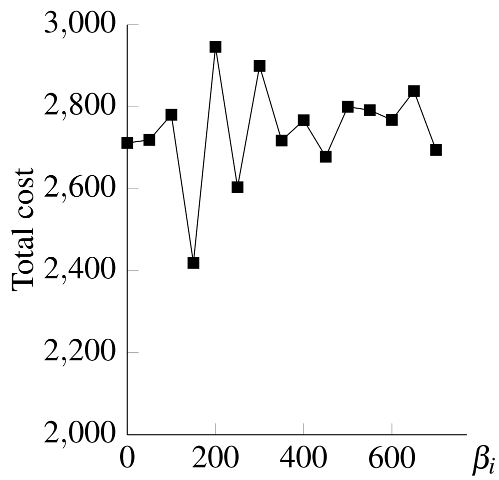


Figure 2.7: Total Cost

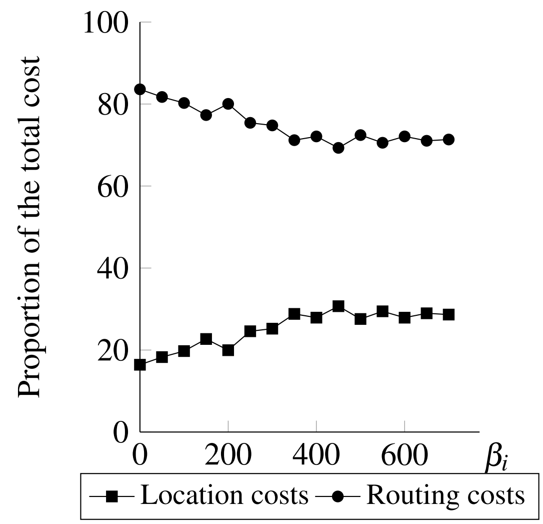


Figure 2.8: Proportion of the Total Cost Associated with Location and Routing Costs

(Figures 2.3–2.6). 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* COV-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. Therefore, increasing the value of β_i does not have an impact on the number of people served due to the number of mobile clinics available and their capacity. Thus, we believe that using the proportion of the population as an indicator allows for a better comparison.

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 2.7 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 2.9 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.

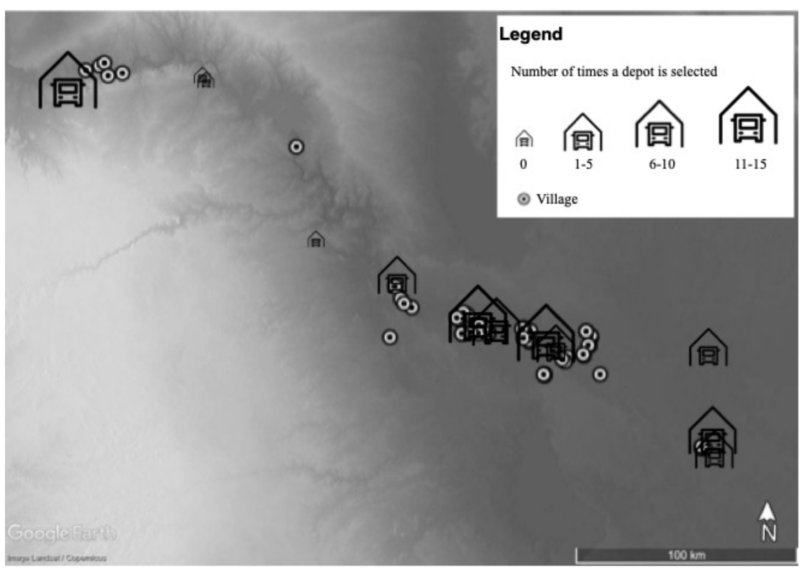


Figure 2.9: Statistics on Selected Depots Related to Coverage

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 COV-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.

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.

First, we analyzed the healthcare performance (Figures 2.10–2.13). 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

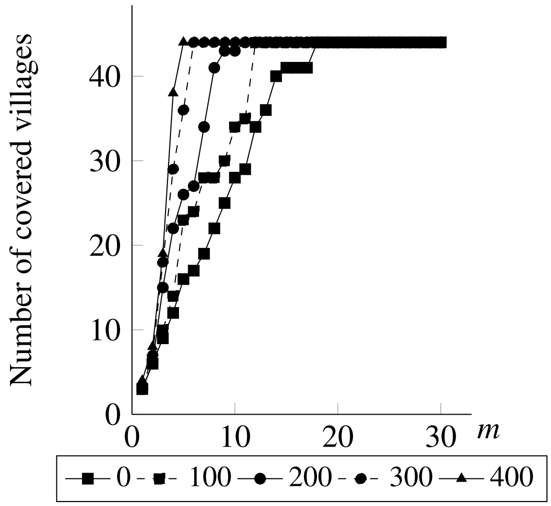


Figure 2.10: Number of Covered Villages ($B = \infty$)

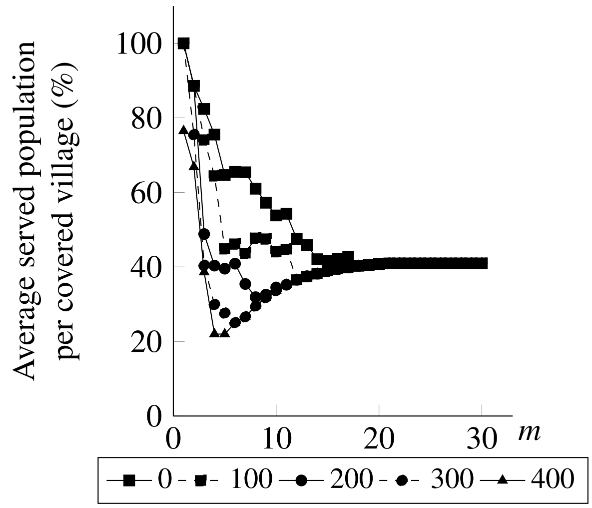


Figure 2.11: Average Proportion of the Population Served at Least **Once** ($B = \infty$)

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, COV-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 2.14 reports the total cost which ranges from \$1,017 with one mobile clinic to \$6,899 with 30 mobile clinics on average. 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 2.15), and with less than 10 mobile clinics, the proportion of the location costs rapidly increases and stabilizes at around 10 mobile clin-

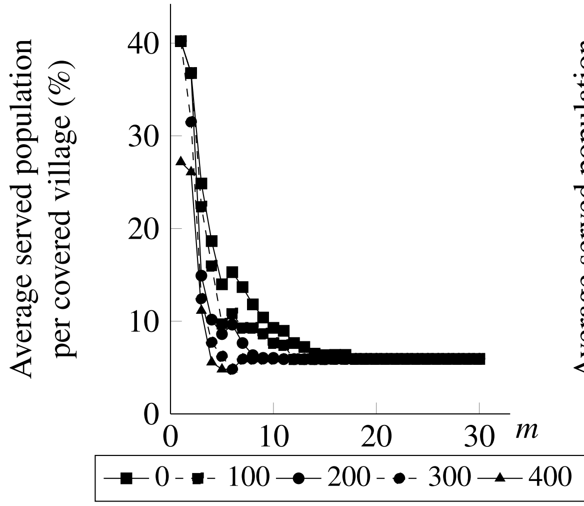


Figure 2.12: Average Proportion of the Population Served at Least **Twice** ($B = \infty$)

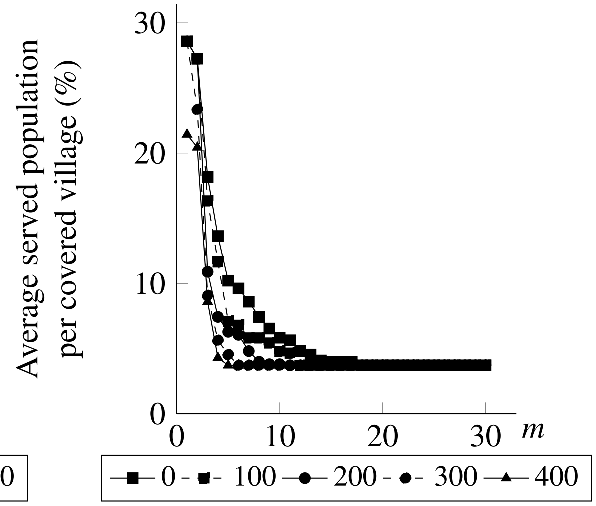


Figure 2.13: Average Proportion of the Population Served at Least **Thrice** ($B = \infty$)

ics. This is explained by the increased number of covered villages for the first 10 mobile clinics (see Figure 2.10). 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 COV-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 dramati-

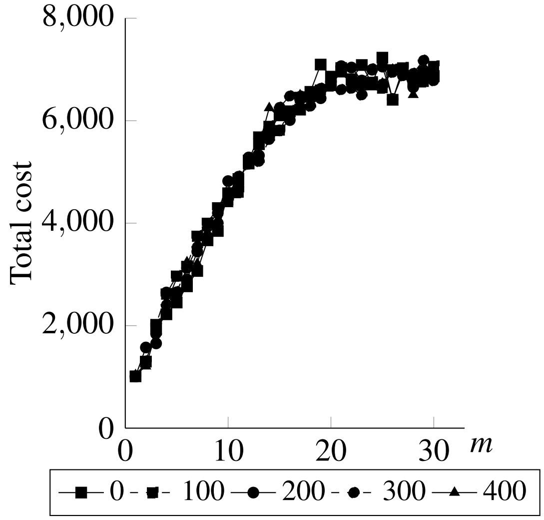


Figure 2.14: Total Cost

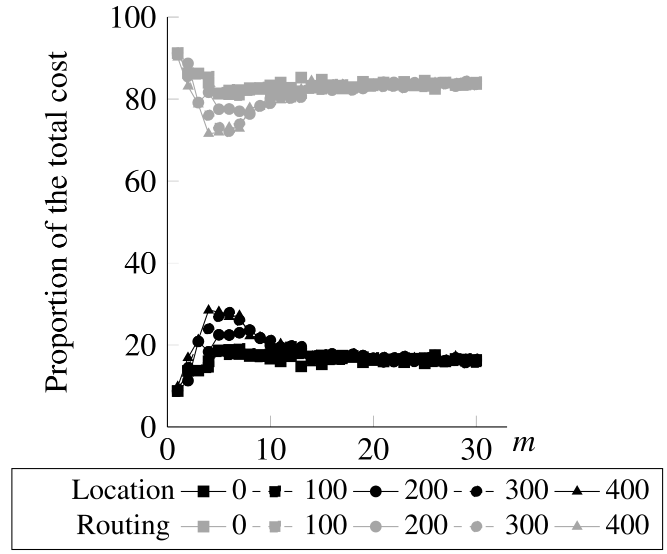


Figure 2.15: Proportion of the Total Cost Associated with Location and Routing Costs

cally the potential impact of the program.

Impact of the continuity of care benefit function

As indicated in Section 2.4.3, 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 $\beta_i^v, \forall i \in \mathscr{N}^c, v \in \mathscr{V}$, 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

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

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

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

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 2.16 and 2.17 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., $|\mathscr{V}| = \{3, 5\}$.

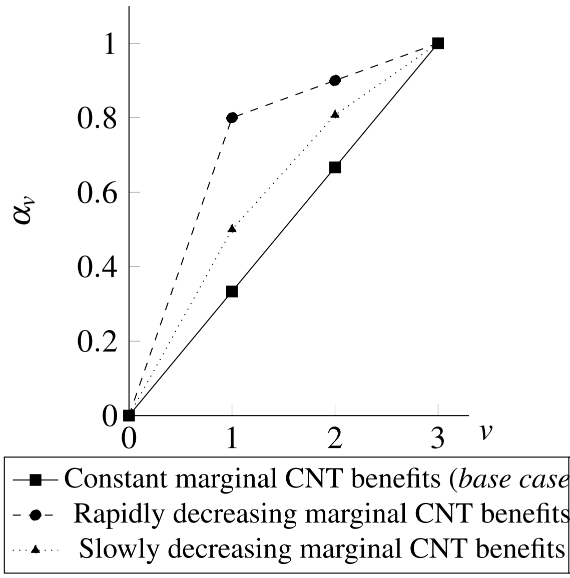


Figure 2.16: Value of α_v According to the Marginal CNT Benefit, $|\mathscr{V}| = 3$

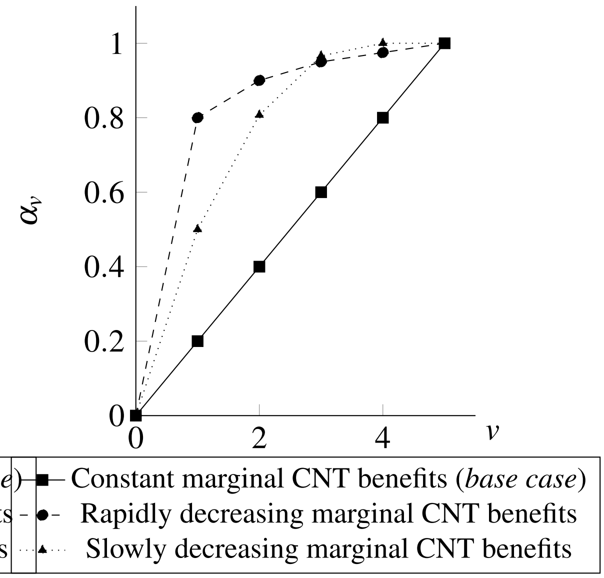


Figure 2.17: Value of α_v According to the Marginal CNT Benefit, $|\mathscr{V}| = 5$

First, we analyzed the performance associated with healthcare (Figures 2.18–2.19). Out of the 50 villages, the number of covered villages ranges from 18 to 30 and from 17 to 41, 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, COV-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 COV-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 COV-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 $\beta_i \geq 100$.

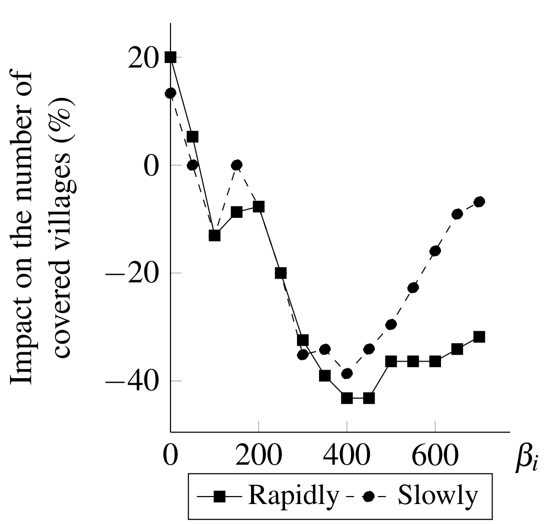


Figure 2.18: Impact on the Number of Covered Villages when Considering Rapidly and Slowly Decreasing Marginal CNT Benefits ($m = 5$, $B = 5{,}000$)

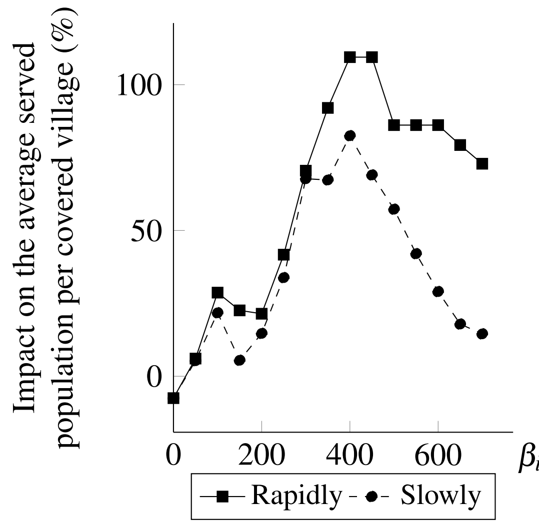


Figure 2.19: Average Proportion of the Population Served at Least **Once** with Rapidly and Slowly Decreasing Marginal CNT Benefits ($m = 5$, $B = 5{,}000$)

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.

Second, we analyzed the logistics performance. Figure 2.22 reports the impact on the total cost (compared with constant marginal CNT benefits), whereas Figure 2.23 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

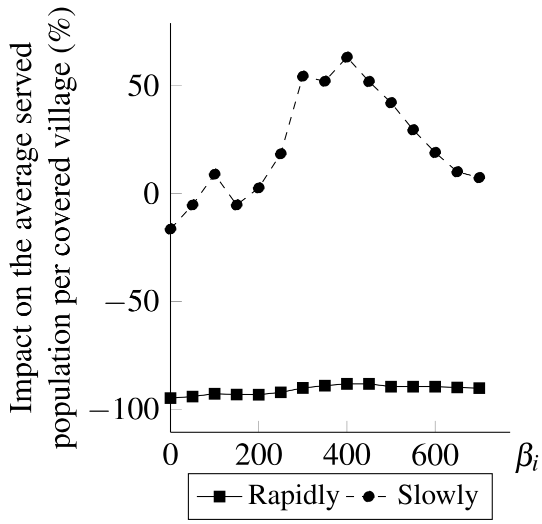


Figure 2.20: Average Proportion of the Population Served at Least **Twice** with Rapidly and Slowly Decreasing Marginal CNT Benefits ($m = 5$, $B = 5,000$)

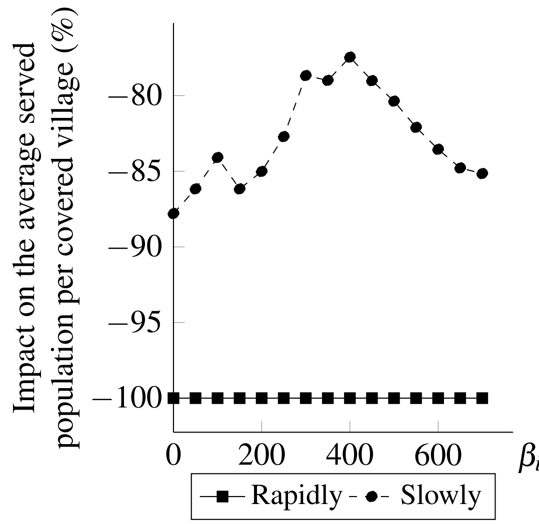


Figure 2.21: Average Proportion of the Population Served at Least **Thrice** with Rapidly and Slowly Decreasing Marginal CNT Benefits ($m = 5$, $B = 5,000$)

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 2.24 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.

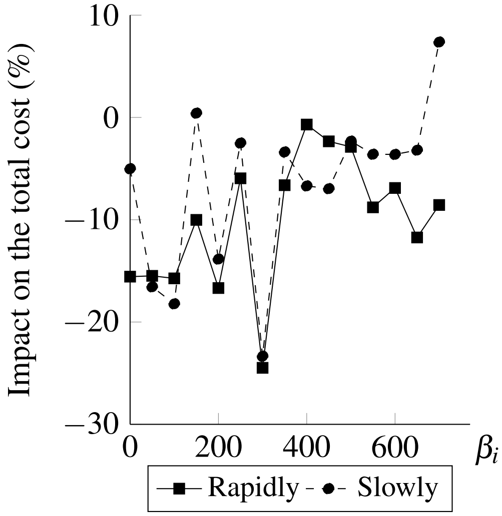


Figure 2.22: Impact on the Total Cost with Rapidly and Slowly Decreasing Marginal CNT Benefits ($m = 5$, $B = 5,000$)

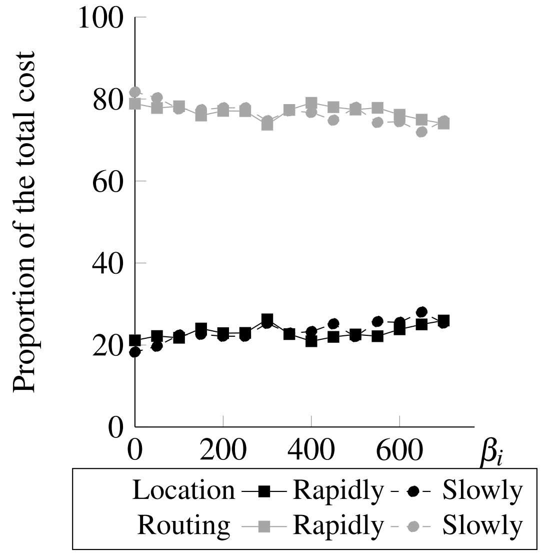
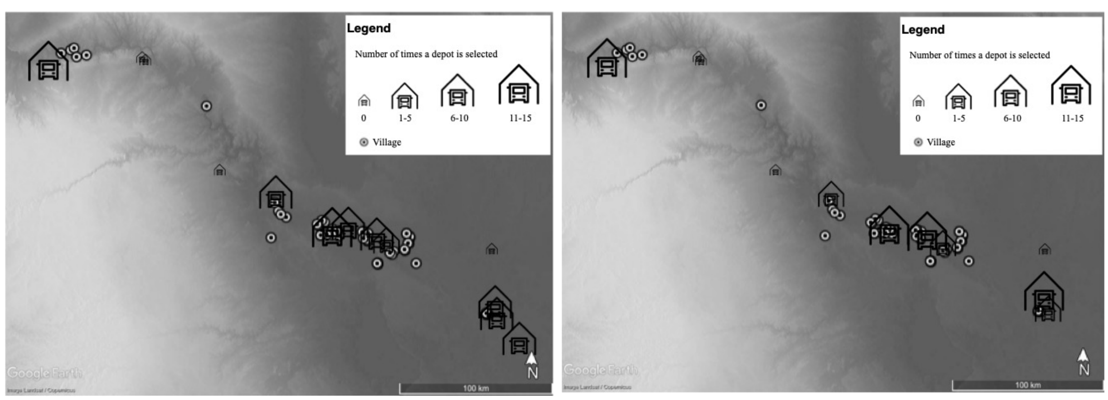


Figure 2.23: Proportion of the Total Cost Associated with Location and Routing Costs with Rapidly and Slowly Decreasing Marginal CNT Benefits ($m = 5$, $B = 5,000$)



(a) Rapidly decreasing marginal CNT benefits

(b) Slowly decreasing marginal CNT benefits

Figure 2.24: Statistics on Selected Depots Related to the Marginal CNT Benefits

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 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.

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 2.4.3), 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) proportional to the population of the villages, denoted as *population proportion* (*Pop.*); 2) proportional to the health score of the villages, denoted as *score proportion* (*Score*); 3) proportional to the vulnerability score (e.g., pregnant women, children, and elderly) of the villages, denoted as *vulnerability proportion* (*Vul.*); and 4) proportional to the accessibility to healthcare of the villages, denoted as *accessibility proportion* (*Acc.*). For example, given the capacity Q, a route r_1 which covers exactly two villages $i_1, j_1 \in \mathscr{N}^c$, 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

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

where p_i is the population seeking healthcare at village i. With *score proportion*, the number of patients served is

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

where s_i is the health score of village i. With *vulnerability proportion*, the number of patients served is

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

where s^1_i is the vulnerability score of village i determined by PUI during the healthcare needs assessment. With *accessibility proportion*, the number of patients served is

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

where s^2_i is the accessibility score of village i computed by PUI during the healthcare needs assessment.

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 2.25–2.28). When $\beta_i = 0$, 15 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., 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, COV-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

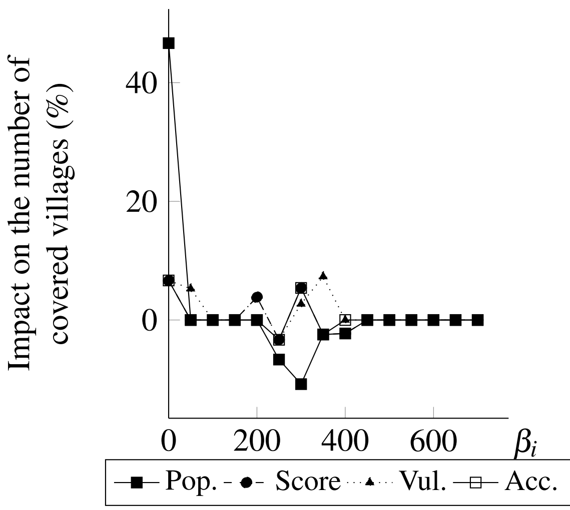


Figure 2.25: Impact on the Number of Covered Villages when Considering the Number of Visits at Each Village ($m = 5$, $B = 5{,}000$)

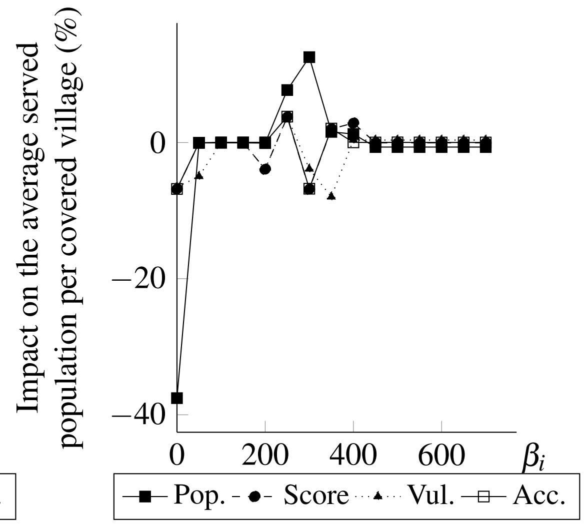


Figure 2.26: Average Proportion of the Population Served at Least **Once** when Considering the Number of Visits at Each Village ($m = 5$, $B = 5{,}000$)

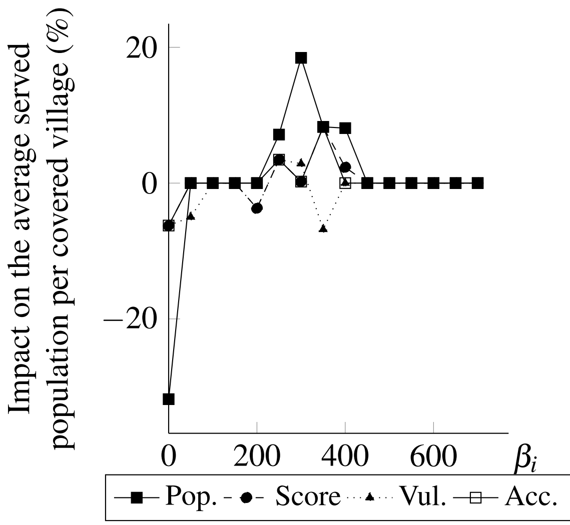


Figure 2.27: Average Proportion of the Population Served at Least **Twice** when Considering the Number of Visits at Each Village ($m = 5$, $B = 5{,}000$)

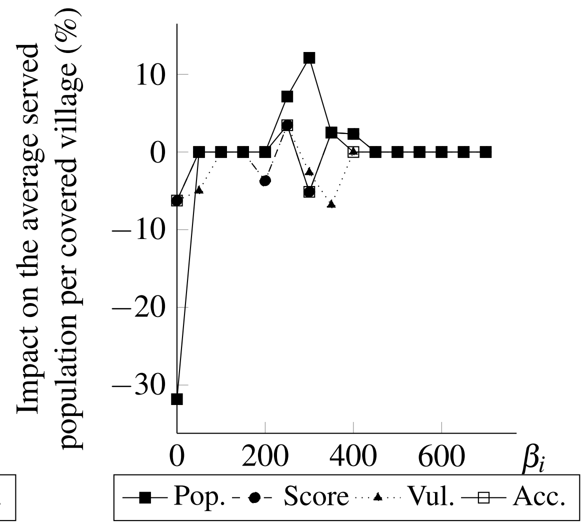


Figure 2.28: Average Proportion of the Population Served at Least **Thrice** when Considering the Nuumber of Visits at Each Village ($m = 5$, $B = 5{,}000$)

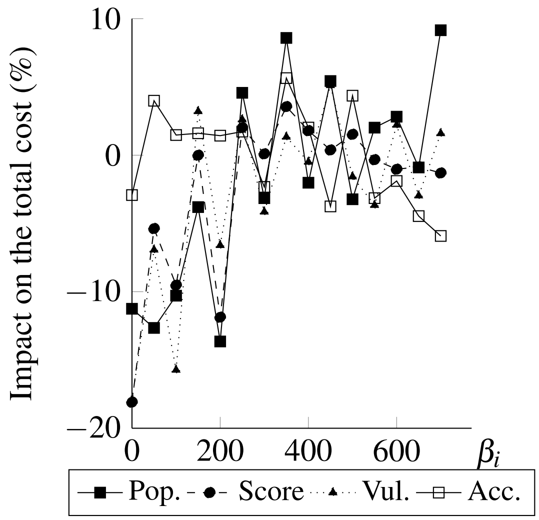


Figure 2.29: Impact on the Total Cost when Considering the Number of Visits at Each Village ($m = 5$, $B = 5,000$)

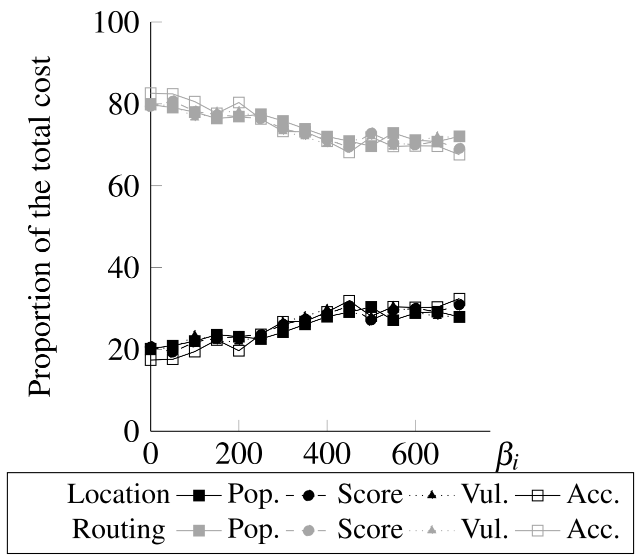
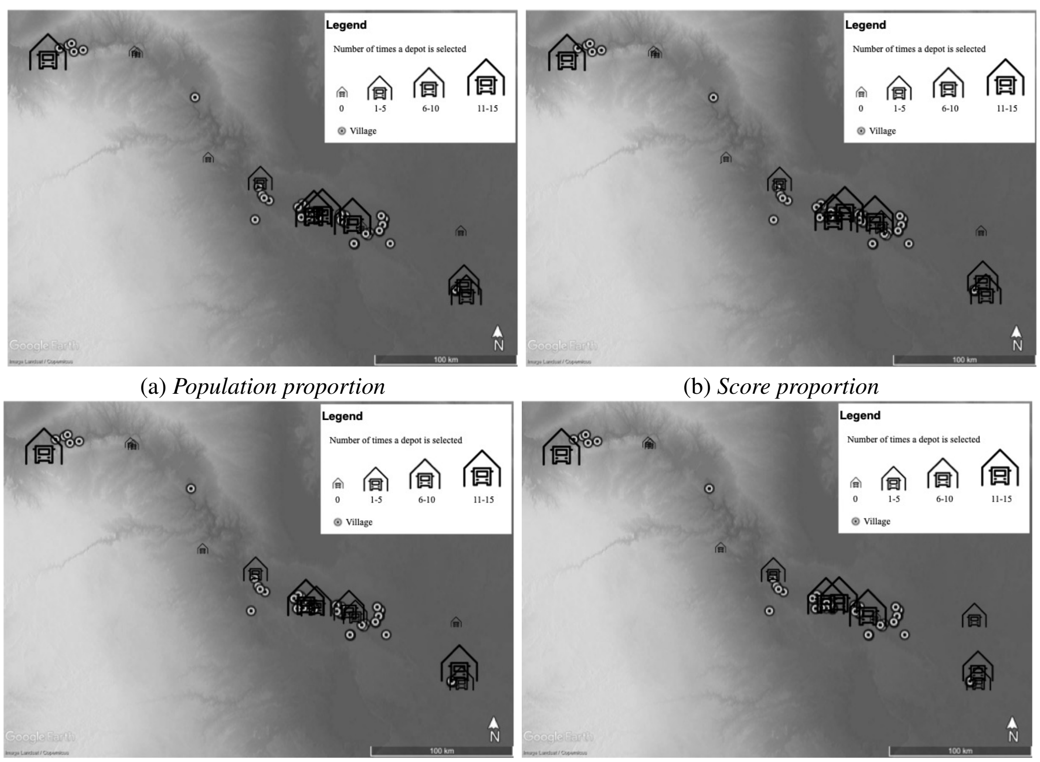


Figure 2.30: Proportion of the Total Cost Associated with Location and Routing Costs when Considering the Number of Visits at Each Village ($m = 5$, $B = 5,000$)

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, COV-1, CNT-2, and CNT-3 remain relatively constant, while we can notice a slight increase of COV-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 2.29 reports the impact on the total cost (compared with *equal proportion*), while Figure 2.30 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 2.31 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 2.31: 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 Appendix **??**. 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.

Impact of allowing all regular routes

As explained in Section 2.4.3, 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.

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 2.32–2.35. 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 COV-1, CNT-2, and CNT-3.

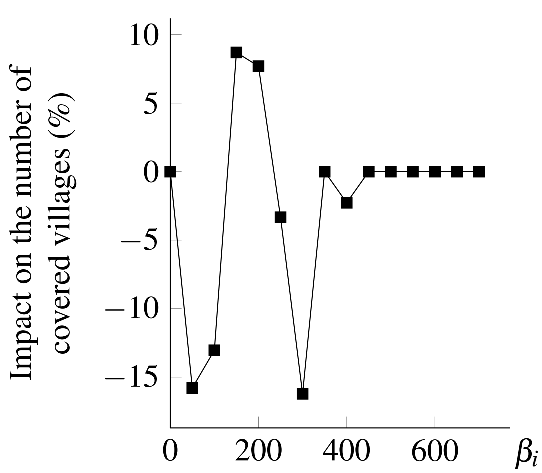


Figure 2.32: Impact on the Number of Covered Villages when Considering Regular Routes Starting and Ending at Different Depots ($m = 5$, $B = 5,000$)

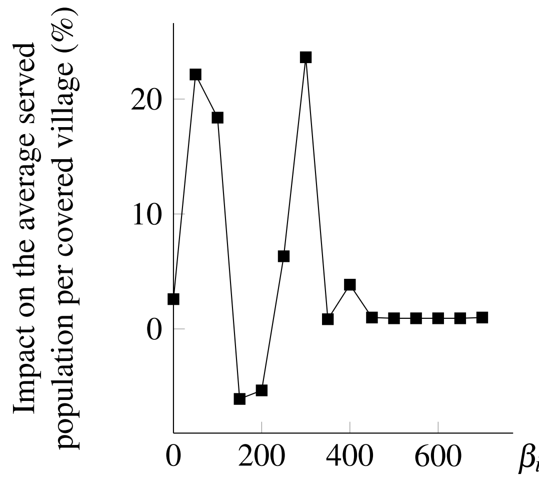


Figure 2.33: Average Proportion of the Population Served at Least **Once** when Considering Regular Routes Starting and Ending at Different Depots ($m = 5$, $B = 5,000$)

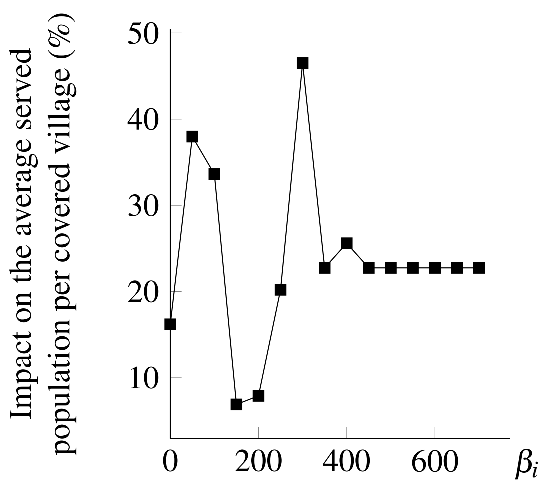


Figure 2.34: Average Proportion of the Population Served at Least **Twice** when Considering Regular Routes Starting and Ending at Different Depots ($m = 5$, $B = 5,000$)

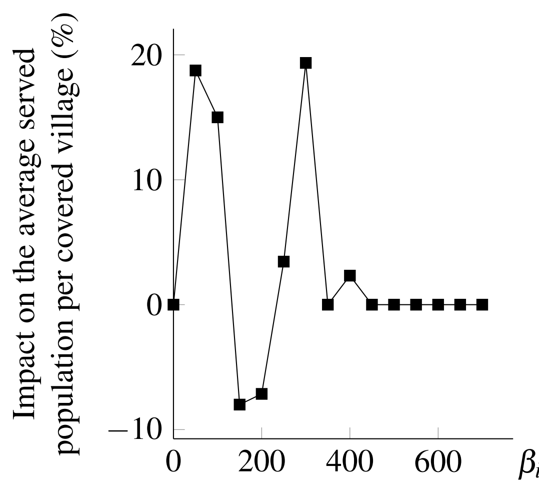


Figure 2.35: Average Proportion of the Population Served at Least **Thrice** when Considering Regular Routes Starting and Ending at Different Depots ($m = 5$, $B = 5,000$)

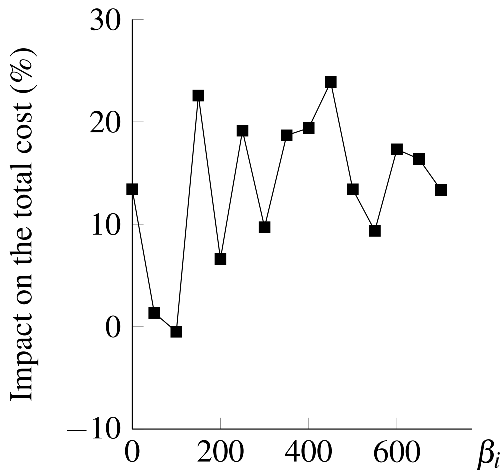


Figure 2.36: Impact on the Total Cost when Considering Regular Routes Starting and Ending at Different Depots ($m = 5$, $B = 5,000$)

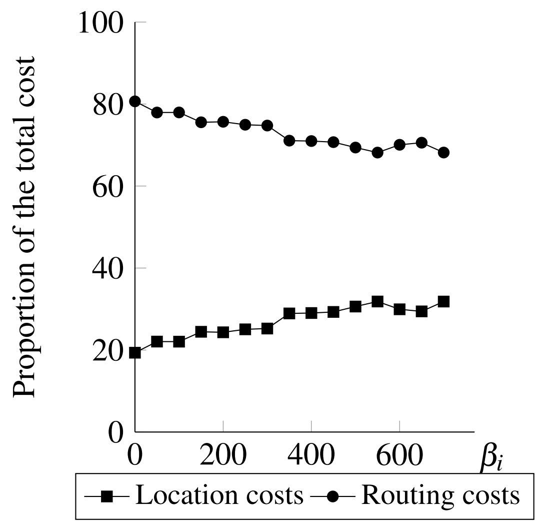


Figure 2.37: Proportion of the Total Cost Associated with Location and Routing Costs when Considering Regular Routes Starting and Ending at Different Depots ($m = 5$, $B = 5,000$)

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 COV-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 COV-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 note an average increase of 8% on the number of covered villages, which results in an average decrease of 6%, 7%, and 8% on COV-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 2.36 and 2.37 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 2.38 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.

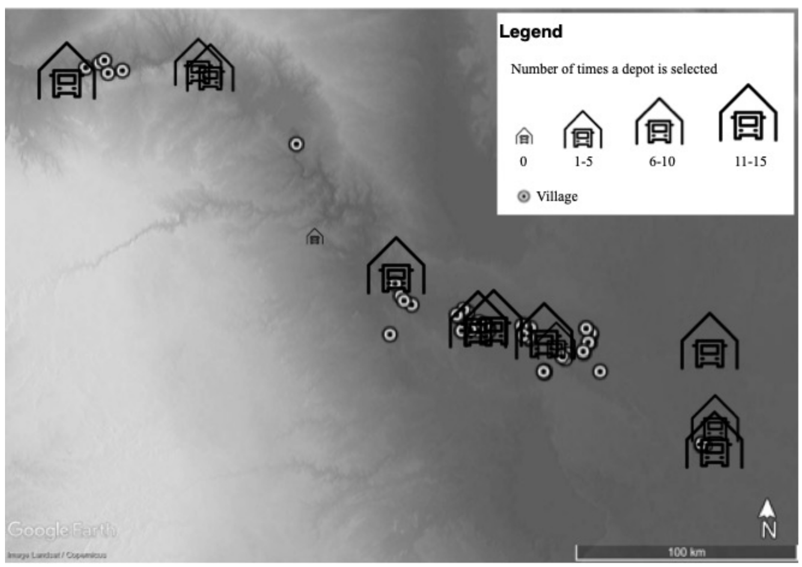


Figure 2.38: Statistics on Selected Depots Related Allowing all Regular Routes

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 limited, this decreases the logistics performance.

2.5 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 benefit, considering both COV and CNT benefits. 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 deployment of mobile clinics.

Our solution approach was tested using real data from our partner (PUI) for a mobile clinic deployment 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, the choice of marginal CNT benefit function, and the ways routes are generated (number of individuals visited at each village in the routes and allowing routes to start and end at different depots). Our results show that increasing the available budget for this humanitarian program, and thus the number of mobile clinics allows to cover more villages. On the other hand, decreasing the current number of mobile clinics in the program would significantly decrease coverage. 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. Similarly, the different policies to determine the number of individuals visited at each village in the routes have a very limited impact on the performance of the deployment. Hence, an equal division between all villages is recommended and is simpler in practice. Finally, allowing routes that start and end at different depots tends to increase continuity of care without decreasing coverage, but this comes at a higher cost.

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 strategic decisions. For example, ending a route at a different depot implies that the medical personnel must be transported back to their vehicles or home locations. On the other hand, the limited resources available only allow for a $5,000 budget and five mobile clinics. Nonetheless, we provided a tool to better understand and quantify the implications of their strategic decisions and different tactical decision policies. With the proposed tool practitioners may explore the effect of a budget or resource increase, for example, without having to spend or invest ahead of time. 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 the problem of mobile clinic deployment to increase outreach to underserved communities and the effectiveness of logistics operations. 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.

Chapter 3

A Stochastic Prize Collection Methodology for Mobile Clinic Deployment Planning

3.1 Introduction

Around 90% of countries surveyed by the World Health Organization (WHO) reported disruptions to health services in 2021 (WHO, 2021). Adhanom Ghebreyesus (2021) stresses that humanitarian organizations must continue to focus on the distribution of services and access to healthcare to meet the 2030 Sustainable Development Goals (UN, 2015a). Humanitarian standards dictate that at least 80% of the population must have access to healthcare services within a one hour walk (Sphere Association, 2018). To correct healthcare disruptions, the WHO proposes the use of mobile clinics as a solution for humanitarian healthcare relief (WHO, 2016b).

Mobile clinics are an intermittent modality used to improve access to healthcare when permanent health facilities are not available (Du Mortier and Coninx, 2007a,b). They consist of vehicles transporting medical equipment and healthcare providers that can offer onsite healthcare services (McGowan et al., 2020). Mobile clinics are a staple in humanitarian contexts but they have become increasingly visible due to COVID-19 (Ali, 2022), as they are well suited to fill healthcare needs during epidemics (Ali, 2022; Alcendor et al., 2022; Levy, 2002; Leibowitz et al., 2021). Studies have also shown that mobile clinics allow for prompt response and flexibility because of the ability to change locations (Wray et al., 1999), and they can be equipped to respond to several health issues (Blackwell and Bosse, 2007). They have also been used to eliminate access barriers and have resulted in improvements in health outcomes and reductions in costs (Oriol et al., 2009; Drake et al., 2015; Malone et al., 2020). Mobile clinics grant vulnerable populations the opportunity to seek healthcare as they remove the difficulties of scheduling an appointment, long waiting lines, and a complex administrative process (Campos and Olmstead-Rose, 2012; Diao et al., 2016; Dasgupta et al., 2015; Kennedy et al., 2014).

Despite their benefits, mobile clinics present logistical challenges and can be operationally expensive (Du Mortier and Coninx, 2007a). Practitioner's material stresses the importance of planning (e.g., mode of action, human and material resources, time frame, and logistics) for a successful deployment (Du Mortier and Coninx, 2007a; ICRC, 2006; WHO, 2021). Furthermore, WHO (2021) highlights the importance of coordination to ensure equity across communities (i.e., no missed or under served communities and no over served communities). Hence, practitioners must plan mobile clinic deployments at the strategic, tactical, and operational levels. At the strategic level, they must select communities, determine the appropriate number of mobile clinics, healthcare practitioners, and medical equipment, and designate a budget (ICRC, 2006; Du Mortier and Coninx, 2007a). Then at the tactical level, they must design a schedule, and decide on the frequency of visits, the days, and the time of day for deployments while respecting the strategical decisions (ICRC, 2006; Du Mortier and Coninx, 2007a). Lastly, at the operational level, they must implement and redact action reports (ICRC, 2006; Du Mortier and Coninx, 2007a). Due to these complexities, Du Mortier and Coninx (2007a) refer to mobile clinics as a “logistical nightmare”.

To exacerbate the challenge of mobile clinic deployment planning for humanitarian relief, Yadav and Barve (2015) stresses that humanitarian supply chains are unstable and unpredictable. According to Hoyos et al. (2015), during humanitarian relief deployments, there is a high risk of infrastructure damage as well as a high probability of secondary disasters. Liberatore et al. (2013) have identified five major parameters affected by uncertainty in humanitarian logistics: demand, demand location, affected areas, supply, and transportation network. A change in these parameters could render a plan inefficient or useless. Therefore, to ensure a robust plan for humanitarian relief deployment, instead of using a deterministic approach uncertainty must be considered in the planning stages (Hoyos et al., 2015). In this study, we address the uncertainty that affects the transportation network and consider demand, demand location, affected areas, and supplies as deterministic. This comes from the premise that before deploying mobile clinics organizations clearly identify their resources, conduct several need assessments at the locations, and maintain a point of contact at the locations (ICRC, 2006).

This paper addresses the need for a decision methodology for mobile clinic deployments that considers the uncertainty faced by practitioners during the tactical planning. As a result, it adapts a Prize Collection Problem (PCP) to define the Stochastic Benefit (i.e., prize) Collection Problem (SBCP). We propose four two-stage models that represent different proposed recourse policies available during mobile clinic deployments. The SBCP consists of two conflicting objectives; the minimization of total costs and the maximization of total profit (Stavropoulou et al., 2019). Authors have highlighted the usefulness of PCP in contexts where resources are not sufficient to serve all the demands (Aksen and Aras, 2006; Archetti et al., 2014). Erdoğan and Laporte (2013) argue that modeling humanitarian deployments as a PCP will allow practitioners to minimize costs while maximizing the total benefit provided to those in need. Hence, the SBCP allows to identify the tactical plan that minimizes the set up and transportation costs associated with providing healthcare services at a given location at specific time period, while at the same time it maximizes the total prize or benefit provided to those in need of humanitarian relief. The methodology is used to systematically evaluate uncertainty which impacts the transportation network in which mobile clinics are deployed. The uncertainty is translated into travel time increases, inaccessible communities, and unusable roads, all of which are time dependent. At the tactical planning level the uncertainty can be predicted by knowledgeable people, herein experts on the field, that can provide an educated update at the beginning of the planning period (e.g., a week) valid for the duration of the deployment. The updated information allows managers to update the tactical plan at the beginning of the schedule length. We study and compare four plan-adjustments (i.e., recourse policies) to tackle uncertainty by either delaying routing decisions, rescheduling along the planning horizon, adjusting routes at each time period, or by not servicing communities that are not accessible. These policies have various levels of flexibility, reliability, and associated cost. We test these policies under different levels of uncertainty (i.e., levels of amplitude in the variations of uncertain parameters) to derive managerial insights on the trade-offs between reliability and flexibility in the mobile clinic tactical deployment plan. The proposed methodology allows to model the impact of new information received before the execution of a tactical plan, the implication of different recourse polices, and the expected costs associated. In what follows, we describe the main decisions and characteristics of mobile clinic deployments for humanitarian relief.

3.1.1 Context and Problem Description

McGowan et al. (2020) highlight that mobile clinics are better suited to offer preventive services, such as vaccinations. Hence we test our methodology in the context of vaccination campaigns for humanitarian relief. Even though we focus on mobile clinic deployments for vaccination campaigns when testing our approach, our contributions and methodology are of general applicability for capacitated mobile clinic deployments. To accurately capture the characteristics of mobile clinic deployments this study relies on material and information shared by field practitioners directly with the authors as part of previous collaboration efforts with humanitarian organizations. Mobile clinic deployments for humanitarian relief are also affected by the uncertainty present in humanitarian logistics (Hoyos et al., 2015). Hence, practitioners are forced to adjust their tactical plans to respond to changes in the transportation network. Based on information previously shared by field practitioners (PUI, 2017d) we define the decision process in mobile clinic deployments affected by uncertainty. First, practitioners design a tactical plan for a determined schedule length that is repeated along the planning horizon (e.g., for a monthly planning horizon a one-week plan, the schedule length, is repeated four times in a month). Before applying the tactical plan (i.e., prior to the beginning of the schedule length), practitioners receive new information by experts on conditions that affect the transportation network (e.g., likelihood of landslides, potential war acts). The new information is translated to a numerical value that allows practitioners to decide if and how the tactical plan must be adjusted. Figure 3.1 provides a representation of the decision time line.

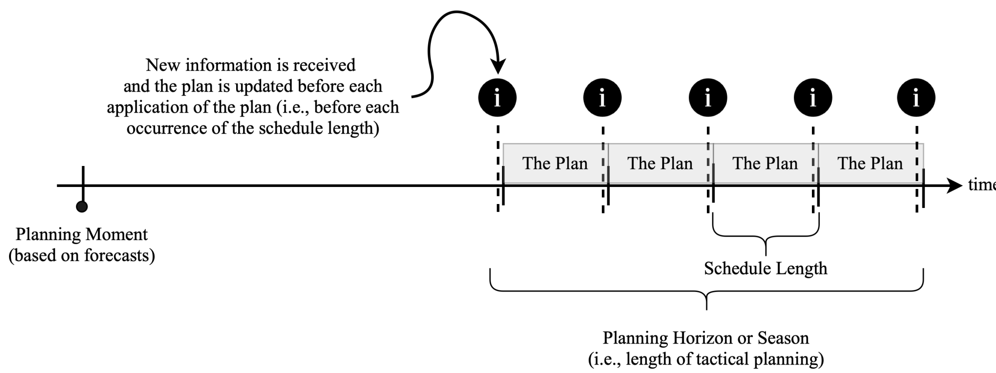


Figure 3.1: Planning Deployments Under Uncertainty

There is an advantage to deciding what communities to visit and notifying those communities a priori when they will be served. The population at the communities in need of healthcare may ensure they are available on the time period the mobile clinic will offer services if the schedule of visits is shared in advance with the point of contact at each community. Hence, practitioners must assess communities and establish points of contact before the planning moment. The point of contact at each community will serve as a liaison that can notify beneficiaries when a mobile clinic will visit and also provide information updates to practitioners before the plan is applied. Community assessments will also aid in the selection of the communities and the time period they will be visited. However, these decisions are subject to change once the field experts provide an update before the beginning of the schedule length on the accessibility to the locations, travel times, and usability of the roads. After the revelation, practitioners are faced with the issue of adjusting the tactical plan. They can decide to not serve some of the communities previously identified or change the time period at which a visit would occur. Finally, if a decision was made on which route to take, it can be adjusted by selecting other path segments or changing the order of stops to be made if the route visits more than one community. This means that an adjusted route can contain a subset of the communities originally scheduled but reached in a different order or through another road. Nonetheless, deciding in advance rather than waiting for the updated predictions allows practitioners to provide reliability to the beneficiaries. Moreover, when tactical decisions (i.e., locations, time periods, and routes) are taken a priori the utilization of resources can be better employed to ensure a maximization of the benefit provided by the mobile clinic deployment.

At the beginning of the planning horizon, the estimated travel time, based on the experts knowledge and distributions, is known and it is assumed that locations are accessible by usable roads. However time, access, and usability are subjected to sources of uncertainty, which can affect the effectiveness and delivery of humanitarian relief (i.e., prize and cost) (Hoyos et al., 2015). Underestimation of travel time can hinder or prevent the timely delivery of relief. Although estimated travel times might be available (with the use of geographical positioning systems (GPS) in a humanitarian context, many factors, such as weather conditions, acts of war, or secondary disasters, may alter estimated travel times. Furthermore, when roads are subjected to natural or human-made disasters they can be rendered unusable and may no longer be considered as part of a route. Hence, a route that contains roads that are no longer usable cannot be used by the mobile clinic. Even if the travel time and usability of the roads remain unchanged, in a humanitarian or disaster context, access to the locations is not guaranteed. For example, security checkpoint personnel may block access to the location if external policymakers find it necessary. Also, an unforeseen event may cause the population to be displaced or unavailable to receive the relief during the scheduled time of delivery.

We model the tactical planning of mobile clinic deployments using a SBCP

(Stavropoulou et al., 2019), an extension of the traveling salesman problem. This problem is well suited to model the trade-off between cost and benefit present in mobile clinic deployments as it can consider the limited availability of resources during humanitarian deployments. The cost component of the SBCP captures the costly nature of mobile clinic deployments (Du Mortier and Coninx, 2007a), while the prize collection component allows to represent the fact that a subset of communities need to be chosen due to limited resources (ICRC, 2006; Du Mortier and Coninx, 2007a). In this study, prize is captured with a Benefit-Cost Ratio (BCR) representing the monetary inflow and outflow (Schwab and Lusztig, 1969). BCRs have been proven to be an effective way to capture benefit offered through healthcare services, with vast documentation on vaccination campaigns (Domingo, 1999; Pathania, 1999; Hsu et al., 2003; Bae et al., 2013; Raj et al., 2019; Teng et al., 2014; Okafor and Ekwunife, 2021). We use a multiperiod planning horizon to capture the time related attributes of the problem and the importance of respecting scheduled times of visits, as inconsistencies can discourage beneficiaries from seeking healthcare (Du Mortier and Coninx, 2007a). Furthermore, a multiperiod modeling approach also allows to represent the time dependency of the effects of uncertainty on the transportation network. In our proposed models, we consider a homogeneous fleet of mobile clinics with equipment and medical staff assigned uniformly. As mobile clinic deployments target a specific healthcare need and, therefore, clinics are equipped to offer the same services (Du Mortier and Coninx, 2007a). Although the model could be adapted to consider multiple depots, a single origin destination is considered as the permanent facility, conforming to the notion that mobile clinics need to be used in conjunction with a fixed facility (ICRC, 2006). Furthermore, the networks studied contain one region with a single depot and there are no intersections among depots (i.e., locations cannot be accessed from more than one depot).

We capture decision making under uncertainty with a two-stage stochastic program, which allows to model the sequence of interrelated decisions (King and Wallace, 2012b), this is consistent with our context. For mobile clinic deployments for humanitarian relief a two-stage program allows us to capture the decisions made before the uncertainty revelation as a first stage and the modification or final decisions before executing a planned schedule as the second stage. These decisions are taken at different stages due to the revelation of uncertainty in the field. The revelation of uncertainty is the form of new information from experts. This information can come in the form of communications from the Ministry of Health of a country, humanitarian action clusters, or a point of contact at a community. The updated information is then translated into a numerical value and used to alter the original tactical plan, while still seeking to maximize total profit (i.e., the difference between total prize collected and costs incurred). To model the uncertainty on the second stage we use a set of scenarios that represent the different realizations (i.e., realities or occurrences), and, therefore, we calculate an expected cost over the set based on the second stage decisions. Using two stage programs allows not only to optimize for the cost of the tactical plan but to also explicitly take into account the costs incurred in plan adjustments due to conditions encountered in the field when applying the tactical plan. This in turn empowers practitioners by providing a methodology that can evaluate the utilization of funds and resources as well as the humanitarian impact on beneficiaries.

King and Wallace (2012a) define the potential options to respond to uncertainty as recourse actions. These recourse actions, which are taken in response to a future event, impact the performance of the deployment as they lead to a cost or benefit (King and Wallace, 2012a). Hence, we propose four different recourse policies, i.e., four distinct two-stage SBCP models, based on practitioner's experiences in the field. These policies are then tested and evaluated to provide insights.

The first policy proposed is the *Select then Route*, which consists of selecting the communities to visit in the first stage, and once the information is revealed the routing and scheduling decision can be made. With this policy the locations to be visited are known at the first stage and can be announced ahead of time but the day on which the location will be visited may only be announced at the beginning of the schedule. This recourse policy, offers flexibility as it does not commit resources to specific days. Also, over a multiperiod, horizon communities and path segments that are not available in a given period can be available on other time periods. Hence, practitioners have the flexibility to select the paths and time periods that allow them to serve as many of the selected communities as possible.

The remaining three policies are based on the option to take all three decisions (i.e., location, routing, and time period) at the planning moment and modifying them according at beginning of the planning horizon based on the information received. The second policy proposed is a *Full Recourse*, reoptimizing the complete plan. This policy allows practitioners to communicate to the communities the time periods at which they will be visited as well as assign drivers to specific routes. However, with the full recourse based on the uncertainty revelation all locations, routes and periods selected are subject to change. Therefore, this policy provides the highest flexibility as all decisions can completely be altered. However, it can also give the impression of not being reliable as the communicated schedules and commitment to routes can be completely altered before deployment.

The third recourse policy proposed is a *Simple Recourse*. This policy is the equivalent to "do nothing", meaning that if a path segment is unusable or a location is no longer accessible these are eliminated from the plan. When a path segment is subjected to a time increase and the additional time still allows for the route to be completed within the time period it will still be used, else it will not be used and locations served using that path (i.e., route segment) will not be visited. This recourse would require fewer adjustments to the original tactical plan. The Simple Recourse policy will provide a level of reliability to the communities that do not experience a change in the path segments that connect them nor in their accessibility. However, practitioners lose the flexibility to adjust the plan and, thus can result in underutilization of resources and beneficiaries unattended.

The fourth recourse policy *Reoptimize per Time Period* consists of only altering routing decisions in the second stage. That means that the selected locations and the time periods at which they are served will remain the same. This policy is meant to provide the maximum reliability as the communities can be sure that if no interruptions occur in the network their communities will be visited as per the original plan. Yet, it is not as flexible as the full recourse as locations can only be visited in the time period selected on the original tactical plan. Studying these policies will allow us to derive managerial insights into the trade-offs between reliability and flexibility when planning for uncertainty. Also, we will be able to identify the best performing policies based on the characteristics and the uncertainty impact on the transportation network.

The SBCP modeled as a two-stage program can realistically capture the characteristics of mobile clinic deployments for humanitarian relief. All four proposed models allow decision makers to select communities, schedules, and routes for mobile clinic deployments. In conjunction, these models can be used to evaluate the impact of recourse decisions on the flexibility and consistency offered, as well as the prize collected and costs incurred.

3.1.2 Contributions

The contributions of this paper are as follows. We extend the deterministic formulation in the previous chapter by modeling mobile clinic deployments as an SBCP seeks to maximize the total expected prize collection. Moreover, the objective of the models proposed in this chapter differ from the previous chapter as they do not consider continuity and coverage but instead quantify in monetary value the benefit offered to beneficiaries. This is the first study to address mobile clinic deployment planning as an SBCP. To the best of our knowledge, this study is the first to propose a stochastic formulation for the PCP. Furthermore, this study is also the first to consider the impact of uncertainty on the transportation network during mobile clinic deployments for humanitarian relief. We consider three uncertain parameters: travel time, usability of the roads, and access to the locations. Studies found in humanitarian and disaster relief literature address only one uncertain parameter, with the exception of one study Li et al. (2012) that addresses two parameters: travel time and accessibility. No studies have previously evaluated or proposed recourse policies in the context of disaster and humanitarian relief. Whereas, we propose four different recourse policies and evaluate their impact on the total profits (i.e., prize collected minus cost), number of locations visited, and evaluate its performance through different levels of uncertainty. Hence, this study is the first to propose and evaluate the impacts of different recourse policies on the performance of relief efforts. The are not many studies such as ours that capture uncertainty over multiple periods in humanitarian relief operations contexts. Our approach is sufficiently general to support any prize collection operation, notwithstanding our model is tested on real world data for the deployment of mobile clinics for humanitarian relief through a vaccination campaign.

The remainder of the paper is organized as follows. Section 3.2, briefly surveys the literature. Section 3.3, presents the modeling approach used and models proposed. Section 3.4, shows the solution method implemented. Section 3.5, outlines the cases, instances and experiments tested, discuses the results, and presents managerial insights. Finally, conclusions drawn are summarized in in Section 3.6.

3.2 Literature Review

Previous studies on humanitarian operations have focused on efficiency and performance to account for scarce resources (Nunes and Pereira, 2021). Holguín-Veras et al. (2012) defined the effectiveness of humanitarian operations as the extent to which it decreases harm, suffering, health burden, distress, or inconvenience caused by crises. One of the gaps in the humanitarian logistics literature lies in the identification of resources and capabilities that will enable organizations to deal with the different kinds, and paces of disasters (Jabbour et al., 2019). In this section, we position the SBCP in the literature and highlight how it contributes to filling the gaps in disaster and humanitarian relief literature. First, we discuss previous studies that have proposed operations research or management science (OR/MS) approaches for mobile clinic deployments. Second, we provide a brief overview of the literature relating to the PCP. Finally, we discuss previous studies that have proposed solution approaches to humanitarian relief operations under uncertainty in the accessibility of locations, travel times, and usability of roads.

3.2.1 Mobile Clinics

The first authors to propose OR/MS approaches for mobile clinics deployment were Hodgson et al. (1998) and Doerner et al. (2007). They addressed mobile clinics deployment for humanitarian relief as a covering tour problem (CTP). In the CTP, mobile clinics are located in villages where the maximum number of patients can access them while respecting a maximal walking distance. Hodgson et al. (1998) aims 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. The deployment of mobile clinics in rural areas has also been addressed as a periodic location routing problem (PLRP) by Savaşer (2017). 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). These authors developed a heuristic and test their model on instances derived from deployment of mobile clinics in Turkey.

In a more recent study, De Vries et al. (2021b) studied the scheduling problem for mobile clinics used for medical screenings as an assignment problem of mobile clinics to clusters of villages. They considered a multiperiod planning horizon and assigned each mobile clinic to a cluster in each planning period. However, as the problem is NP hard in nature, (De Vries et al., 2021b) propose heuristics and a column generation approach to solve the model. The authors test their methods with instances from the Democratic Republic of Congo. Furthermore, De Vries et al. (2021a) study the frequency of site visits by mobile clinics. The authors propose an assignment model to determine the number of full day visits to each site during a monthly planning horizon to maximize the number of total expected beneficiaries. The authors test the exact method and four proposed heuristics/policies proposed on instances from Madagascar, Uganda, and Zimbabwe.

Our study is the first to present managerial insights on how the different networks in which mobile clinics are deployed impact the performance of humanitarian relief. Additionally, it is the first to consider the uncertainty that deployments of mobile clinics are subjected to and to propose different recourse policies. Due to the volatile and unpredictable environments in which humanitarian relief is often delivered (Hoyos et al., 2015), considering uncertainty in the transportation network is an added value to mobile clinic deployment tools. Unlike previous studies, we are the first to model the deployment of mobile clinics as a PCP. Additionally, previous studies seek to cover all sites, our approach selects a subset of the locations based on the prize collected at each location while also considering the budgetary restrictions often imposed on humanitarian relief operations. Moreover, we propose a set packing formulation that allows for an exact solution approach whereas previous authors resort to heuristics.

3.2.2 Prize Collecting Problem

The PCP derives from the Traveling Salesman Problem (TSP) (Balas, 2007). The objective of the PCP is to minimize traveling costs and penalty costs while simultaneously maximizing the prize collected. It has been referred to as a TSP with profits by Feillet et al. (2005a). It was first introduced by Balas (1989) as the Prize Collecting Traveling Salesman Problem, in which the salesman gets a prize for every city visited and pays a penalty for every city it fails to visit. However, most authors use null penalty terms in their applications (Feillet et al., 2005b).

Studies of the PCP include applications in which it is not possible to satisfy all the demand due to logistics constraints Feillet et al. (2005b). The majority of the prize collecting literature has been theoretical (Vansteenwegen et al., 2011a) but some studies have showcased different applications. Feillet et al. (2005a) study a car industry freight transportation planning application. They propose a multi vehicle arc routing formulation and obtain solutions with a branch-and-price approach. Similarly, Aráoz et al. (2009) modeled the collection of recycling bins by a private company as a PCP, using an arc routing formulation. The prize collecting literature is also scarce in humanitarian logistics or healthcare applications despite (Erdoğan and Laporte, 2013) highlighting the benefit of said modeling technique in humanitarian contexts. To the best of our knowledge, our study is the first to illustrate the PCP with a real world humanitarian logistics and healthcare application. Also, our study would be the first to propose a real world application of the PCP in which the penalty is not set to null. Moreover, our study would be the first to examine the application of a PCP under uncertainty and propose a formulation for the SBCP.

3.2.3 Humanitarian and Disaster Relief Under Uncertainty

In this section we discuss articles that consider uncertainty in accessibility to locations, travel time, and usability of roads. For detailed surveys on humanitarian and disaster relief literature under uncertainty please refer to Liberatore et al. (2013), Hoyos et al. (2015), and Grass and Fischer (2016a).

Two studies have previously considered uncertainty in the access to locations (Li et al., 2012) and (Noyan et al., 2016). Li et al. (2012) consider uncertainty in both accessibility and travel time. The authors propose a two-stage stochastic model to select the location of shelters and the number of evacuees allocated to these shelters. In their study, they consider a range of possible hurricane events and evacuation needs. Their model seeks to minimize the weighted sum of unmet expected shelter demand and expected total network travel time. They identified 100 hurricane scenarios and test the proposed model on instances generated from the North Carolina American Red Cross list of potential shelters. Noyan et al. (2016) study the stochastic last mile relief network design problem. The two-stage stochastic model proposed by them aims to locate distribution points so that every affected person has access to first aid supply. The objective of their formulation maximizes the expected total accessibility. They developed a solution algorithm and test their method on instances derived from the 2011 earthquake in Turkey.

Travel time uncertainty is more commonly studied in the literature. Andreas and Smith (2009) proposed a linear mathematical model to design evacuation tree networks. Their model seeks to minimize the expected penalty of evacuation. They capture the uncertainty through scenario generation. Due to the complexity of their problem the authors result in an algorithm based on Benders decomposition and an additional algorithm based on primal and dual subproblem solutions. They tested their methods on randomly generated instances. Ng and Waller (2009) propose a stochastic programming-based model to design solutions for transportation networks in light of possible emergency evacuations. The objective of their model minimizes the cost of capacity expansion and expected evacuation time. They test their model on eight scenarios of hypothetical instances. However, they use a convex optimization algorithm to solve larger instances. Liu et al. (2009) developed a two stage stochastic model for allocating limited retrofit resources over multiple highway bridges to improve the resilience and robustness of the transportation system in the face of a disaster. They seek to minimize the weighted sum of the expected costs and the risk. They use a progressive hedging-based heuristic method to solve the Sioux Fall City network instances and an instance derived from the California Alameda County road network. Ahmadi et al. (2015) propose a two stage mathematical model to ascertain the locations of distribution centers. With their objective function, they seek to minimize the penalty cost of unsatisfied demand and fixed costs of opening distribution centers. Because of the large scale of the problem they use a variable neighborhood search heuristic for the multi-depot location-routing problem. Finally, they present results for instances derived from the US Census 2000 and secondary traffic data of San Francisco, California. Tofighi et al. (2016) combine scenario-based approach with possibilistic distributions to address a two-echelon humanitarian logistics network design problem. The model seeks to minimize the total costs of selected central warehouses and local distribution centers, inventory costs, and the expected value of the second stage's objective function with respect to the possible disaster scenarios. The authors transform their fuzzy-based multi-objective model into an equivalent deterministic single-objective problem to apply an evolution heuristic. Their model was tested on five artificial instances and one instance derived from the case of Tehran.

As far as we know, only one study considers uncertainty in the usability of roads. Rath et al. (2016) proposed a two-stage stochastic model to determine the location of depots during disaster relief operations. They consider uncertainty in the usability of the road network attributed to road recovery or ongoing threads, such as floods. Rath et al. (2016) capture the uncertainty through the generation of different scenarios where travel times are affected. The objective of their model seeks to maximize the coverage provided and minimize the total costs. They test their proposed model on a set of artificial instances.

To the best of our knowledge, our study is the first to consider uncertainty simultaneously on all three parameters; accessibility to locations, travel time, and usability of roads. Only one study combines two or more of the uncertainty sources, Li et al. (2012) studies travel time and accessibility to locations. There is a dearth of articles that study the effect of recourse policies in humanitarian or disaster relief (Grass and Fischer, 2016b). Our study aims to fill this gap in the literature by studying four different recourse policies (i.e., simple recourse, select-then-route, re-route per time period, and full network recourse). Furthermore, Grass and Fischer (2016b) highlight that the literature is wanting in studies that take into account multi-disasters and multiperiods. Our study addresses both gaps in the literature as it considers a multiperiod planning horizon and the possibility of multiple disasters reflected in accessibility to locations, and usability of roads.

3.3 Modeling Mobile Clinic Deployments

We model the deployment of mobile clinics under uncertainty in humanitarian contexts as an SBCP with a two-stage program. The first stage builds the initial tactical plan before the revelation of updated information. During the first stage, communities to be served are selected, as well as what routes will be used and at what time periods communities will be visited. After the first stage decisions have been taken, experts provide information updates that are translated into numerical information on accessibility to the locations, travel times, and usability of the roads. This numerical information is then used to alter the plan through the second stage decisions. In the present paper, we assume that uncertainty revelation can result in a travel time increment but not a decrease, as a reduction in travel time is not considered a negative consequence whereas more time spent on the road rather than providing services is of detrimental consequence for the collection of the prize (i.e., less beneficial for the population). The non-usability of the roads is represented by an infinite travel time for each road affected by external factors and as consequence deemed unusable. The accessibility of the community is not guaranteed during all time periods and it is captured by removing the node representing the community and paths connecting it from the network at the corresponding time period, as it is not possible to pass by the location.

To facilitate the comprehension of the modeling process, we first describe the recourse policies with an illustrative example. Then, we enumerate the notation used for the proposed mathematical models. Afterward, we model the problem as a deterministic single-scenario formulation, as this will be used to illustrate and study the impact of uncertainty. Finally, we present the four proposed two-stage SBCP models that capture all different recourse policies studied.

3.3.1 Recourse Policies

To illustrate how the uncertainty is reflected on the network, we present a small example with one departure point and five communities to in Figure 3.2. On the figure, it can be observed that at the planning moment forecasts are available to practitioners on the state of the network (i.e., paths available, travel time, and accessible locations). However, the state of the network is updated with new information received before applying the plan on the schedule length that may require the use of an adjustment policy.

After the information on the state of the network is updated practitioners must decide how the tactical plan will be altered. We propose and evaluate four different recourse policies each captured by different two-stage SBCP models that are illustrated with the

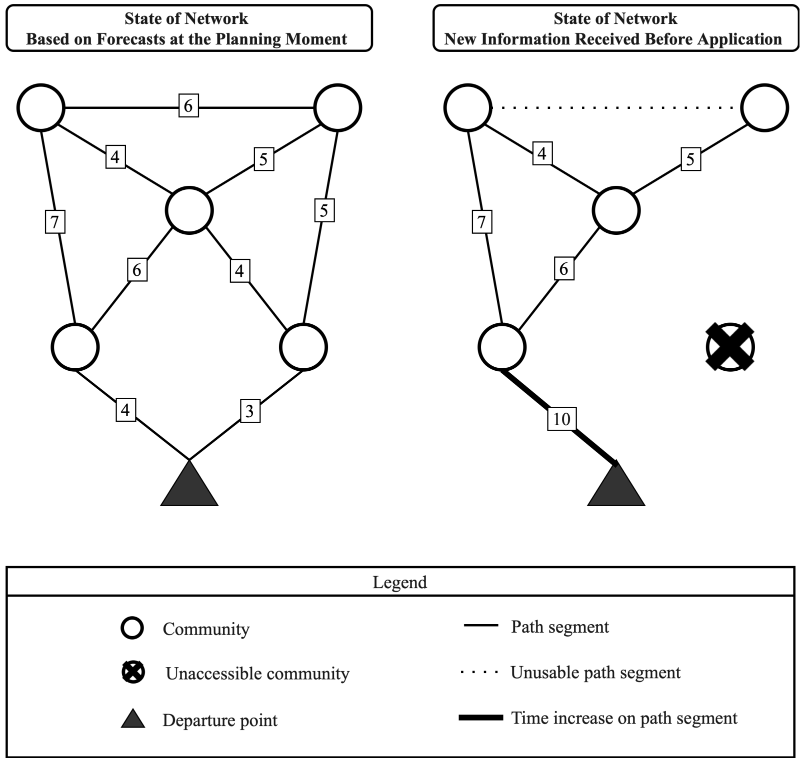


Figure 3.2: Illustrative Example of Uncertainty Impact on the Network

example network with a single time period horizon. The select then route policy selects the communities during the first stage ($t = 0$) and in the second stage selects the routes and time periods at which each community will be visited (see Figure 3.3). In the first stage full recourse, simple recourse, and reoptimize per time period policies share the same first stage decisions (i.e., selection, routing, and time period). However, the policies differ in the decisions during the second stage. Full recourse allows for a complete reselection of routes through the planning period (see Figure 3.4), villages can be visited at another time period, which is not the case for reoptimize per time period. Simple recourse is captured by eliminating all routes (i.e., sequence of stops and path segments) if the revelation of uncertainty renders it infeasible. Yet, during the simple recourse communities are not rescheduled during a different time period (see Figure 3.5). Finally, reoptimize per time period is captured by adding a constraint that ensures communities are visited on the originally selected time period only (See Figure 3.6), although the example may resemble the full recourse policy results might differ. These four policies are illustrated with Figures 3.3 through 3.6 based on the network states presented in the illustrative example on Figure 3.2.

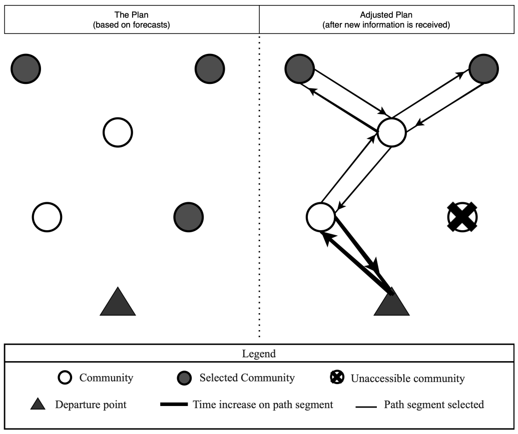


Figure 3.3: Routing on Second Stage Policy

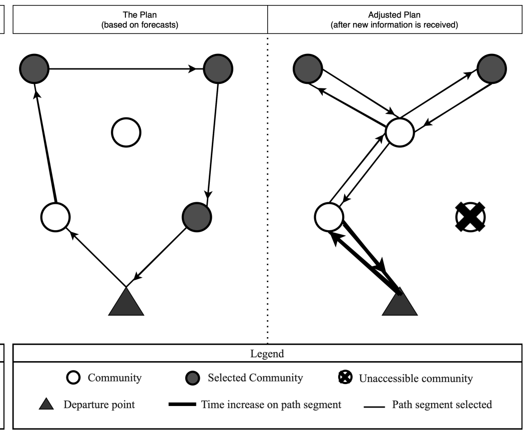


Figure 3.4: Full Recourse Policy

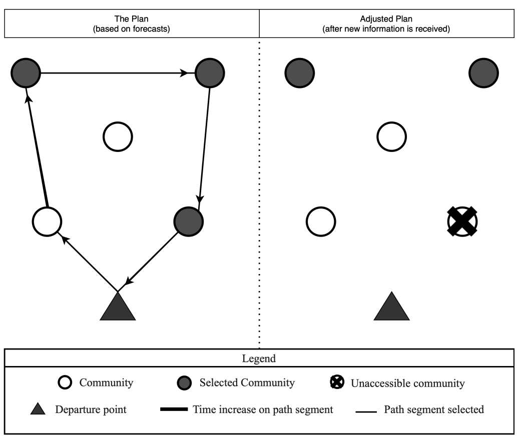


Figure 3.5: Simple Recourse Policy

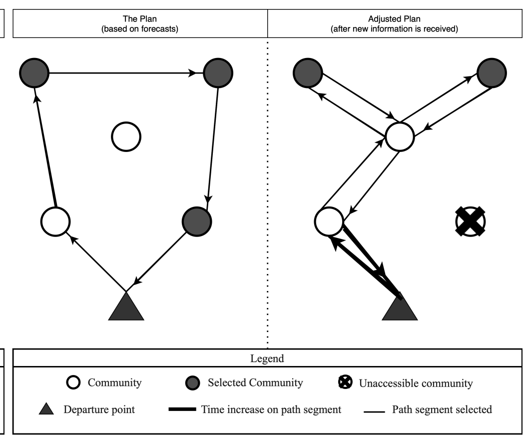


Figure 3.6: Reoptimize per Time Period Policy

3.3.2 Notation

The two-stage Stochastic-Prize Collection Problem is defined on a graph $\mathscr{G} = (\mathscr{N}^c, \mathscr{A})$, where $\mathscr{N}^c$ is the set of nodes representing the depot (i_0) and locations where service will be provided from, and $\mathscr{A}$ is the arc set connecting the depot and the locations. Each location $i \in \mathscr{N}^c$ is associated with a prize $p_i \geq 0$ derived from needs at each location. The fixed cost of servicing a location $i \in \mathscr{N}^c$ is given by f_i. The arc set is defined as $\mathscr{A} = \{(i,j) : i,j \in \mathscr{N}^c\}$ and each arc $(i,j) \in \mathscr{A}$ is associated with a distance d_{ij}. A homogeneous fleet of m capacitated vehicles is available, where the capacity Q of a vehicle is defined as the number of beneficiaries it can service at each time period. Let $\mathscr{T} = \{1,...,t\}$ be the set of time periods of the planning horizon. The total costs of the deployment may not exceed the budget B.

The Stochastic Benefit-Collection Problem is formulated as a set-packing formulation that seeks to maximize the total benefits. The uncertainty is included through a scenario based formulation, where scenarios represent possible realizations of uncertain parameters. Hence, let $S = \{1,...,s\}$ be the set of scenarios with a probability p^s of occurrence per scenario $s \in S$. Let $\mathscr{R} = \{1,...,r\}$ denote the set of possible routes, such that $\mathscr{R} = \cup_{t \in \mathscr{T}} \cup_{s \in S} \mathscr{R}^{ts}$, where $\mathscr{R}^{ts}$ is the set of feasible routes at time period $t \in \mathscr{T}$ for scenario s. Each route $r \in \mathscr{R}$ is defined as an ordered vector of vertices $(i_1, i_2, ..., i_{n-1}, i_n)$ starting and ending at the depot, i.e., $i_1 = i_n = i_0 \in \mathscr{N}^c$, and visiting a subset of locations, i.e., $\{i_2, ..., i_{n-1}\} \in \mathscr{N}^c \setminus \{i_0\}$. Each generated route respects a maximal travel time δ, which includes the travel time, the service time (γ), and the setup time at each location θ. Each route $r \in \mathscr{R}$ defined by a binary vector a_{ir} equal to one if route $r \in \mathscr{R}$ visits a location $i \in \mathscr{N}^c$ and zero otherwise. The cost c_{rt} represents the transportation costs associated with each route $r \in \mathscr{R}$ at a time period $t \in \mathscr{T}$. The transportation cost c^s_{rt} reflects the cost per each scenario $s \in S$. The potential prize to be collected per route $r \in \mathscr{R}$ is also computed to P^s_r for each scenario $s \in S$. The penalty cost ρ^s_{rt} is defined as the cost of not performing route $r \in \mathscr{R}$, if the route was selected, during the time period $t \in \mathscr{T}$ in scenario $s \in S$.

To formulate the problem, we use the first stage binary variables x_i equal to one if location $i \in \mathscr{N}^c$ is selected to be serviced, and equal to zero otherwise, and y_{rt} equal to one if route $r \in \mathscr{R}$ is selected during period $t \in \mathscr{T}$, and equal to zero otherwise. Finally, we use the second stage binary variables λ^s_{rt} equal to one if route $r \in \mathscr{R}$ is selected during period $t \in \mathscr{T}$ in scenario $s \in S$, and equal to zero otherwise, and w_{rt}^s equal to one if selected route $r \in \mathscr{R}$ on the first stage is not used at time $t \in \mathscr{T}$ on the second stage in scenario $s \in S$, and equal to zero otherwise.

3.3.3 Deterministic Model

To grasp the impact of modeling uncertainty, both the mathematical implications as well as the performance of tactical plans under uncertainty, we present the deterministic version of the problem, where the uncertain parameters are set to the estimates available (often but not always the estimated mean) at the planing moment.

$$\text{maximize} \sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} P_r y_{rt} - \sum_{i\in\mathscr{N}^c} f_i x_i - \sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} c_{rt} y_{rt} \tag{3.1}$$

$$\sum_{i\in\mathscr{N}^c} f_i x_i + \sum_{t\in\mathscr{T}}\sum_{r\in\mathscr{R}} c_r y_{rt} \le B, \tag{3.2}$$

$$\sum_{r\in\mathscr{R}} y_{rt} \le m,\ \forall t \in \mathscr{T}, \tag{3.3}$$

$$\sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} a_{ir} y_{rt} = x_i,\ \forall i \in \mathscr{N}^c, \tag{3.4}$$

$$x_i \in \{0,1\},\ \forall i \in \mathscr{N}^c, \tag{3.5}$$

$$y_{rt} \in \{0,1\},\ \forall r \in \mathscr{R}, t \in \mathscr{T}. \tag{3.6}$$

The objective function (3.1) maximizes the total profit and benefit collected with the selected routes minus the cost of servicing a location and performing a route. Constraint (3.2) imposes the budget available for the deployment during the planning horizon. Constraints (3.3) ensure that the number of routes selected during each time period does not exceed the available vehicles. Constraints (3.4) impose that only selected locations are covered only once in only one route. Finally, constraints (3.5) and (3.6) define the variable domain.

3.3.4 Stochastic Models

In the SBCP, each scenario stands for a possible information update in the form of expert knowledge, which is translated into updated travel times on the roads, usability of the road, and access to locations. The travel times, usability, and accessibility are used to generate the set of feasible routes $\mathscr{R}^{ts}$ per time period $t \in \mathscr{T}$ per scenario $s \in S$. The objective is to maximize the collected prize at the selected locations while also accounting for the cost of coordination at the locations (e.g., contacting leaders at the locations and identifying sites), the cost of transportation, and the expected cost of plan adjustments.

Routing on Second Stage

For the two-stage SBCP with routing on the second stage, the locations from where the prize will be collected are selected on the first stage and routing decisions are taken on the second stage. Hence, the two-stage stochastic prize collection problem with routing on the second stage can be modeled as follows.

$$\text{maximize } -\sum_{i\in\mathscr{N}^c} f_i x_i + E_\xi\left[Q(x,\xi(\omega))\right] \tag{3.7}$$

$$x_i \in \{0,1\},\ \forall i \in \mathscr{N}^c, \tag{3.8}$$

where:

$$E_\xi\left[Q(x,\xi(\omega))\right] = \max_{\lambda_{rt}(\omega)} \sum_{s\in S} p^s \sum_{r\in\mathscr{R}} \sum_{t\in\mathscr{T}} \left(P^s_{rt} - C^s_{rt}\right)\lambda^s_{rt} \tag{3.9}$$

s.t.

$$\sum_{i\in\mathscr{N}^c} f_i x_i + \sum_{r\in\mathscr{R}} \sum_{t\in\mathscr{T}} c^s_{rt}\lambda^s_{rt} \le B, \forall s \in S, \tag{3.10}$$

$$\sum_{r\in\mathscr{R}} \lambda_{rt}^s \leq m,\ \forall t \in \mathscr{T},\ \forall s \in S, \tag{3.11}$$

$$\sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} a_{ir}\lambda_{rt}^s \leq x_i,\ \forall i \in \mathscr{N}^c,\ \forall s \in S, \tag{3.12}$$

$$\lambda_{rt}^s \in \{0,1\},\ \forall r \in \mathscr{R}, t \in \mathscr{T},\ \forall s \in S. \tag{3.13}$$

The objective function (3.7) maximizes the total expected profit, prize collected at the selected locations minus the cost of selecting the location and routing cost realization. Where the objective function (3.9) maximizes the sum of the cost associated prizes minus the routing costs. Constraint (3.10) imposes the budget available for the deployment during the planning horizon. Constraints (3.11) ensure that the number of routes selected during each time period does not exceed the available vehicles. Constraints (3.12) impose that only the selected locations are covered and are covered only once. Finally, constraints (3.8) and (3.13) define the variable domains.

3.3.5 Routing on First and Second Stage

In the two-stage Prize Collection with routing decisions on both the first and the second stage, the locations $i \in \mathscr{N}^c$ from where services will be provided and the routes $r \in \mathscr{R}$ used at $t \in \mathscr{T}$ are selected on the first stage. However, the routes are subjected to change after the revelation of the updated information in the second stage. Therefore, the two-stage Prize Collection with routing on the first and second stage can be modeled as follows.

$$\text{maximize } -\sum_{i\in\mathscr{N}^c} f_i x_i + \sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} P_r y_{rt} + E_\xi\left[Q(x,\xi(\omega))\right] \tag{3.14}$$

s.t.

$$\sum_{i\in\mathscr{N}^c} f_i x_i + \sum_{t\in\mathscr{T}}\sum_{r\in\mathscr{R}} c_r y_{rt} \leq B, \tag{3.15}$$

$$\sum_{r\in\mathscr{R}} y_{rt} \leq m,\ \forall t \in \mathscr{T}, \tag{3.16}$$

$$\sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} a_{ir}y_{rt} = x_i,\ \forall i \in \mathscr{N}^c, \tag{3.17}$$

$$x_i \in \{0,1\},\ \forall i \in \mathscr{N}^c, \tag{3.18}$$

$$y_{rt} \in \{0,1\},\ \forall r \in \mathscr{R}, t \in \mathscr{T}, \tag{3.19}$$

where:

$$E_\xi\left[Q(x,\xi(\omega))\right] = \max_{\lambda_{rt}(\omega)} \sum_{s\in S} p^s \sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} (P^s_{rt} - C^s_{rt})\,\lambda^s_{rt} - \rho^s_{rt} w^s_{rt} \tag{3.20}$$

s.t.

$$\sum_{i\in\mathscr{N}^c} f_i x_i + \sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} c^s_{rt}\lambda^s_{rt} \leq B, \forall s \in S \tag{3.21}$$

$$\sum_{r\in\mathscr{R}} \lambda^s_{rt} \leq m,\ \forall t \in \mathscr{T},\ \forall s \in S, \tag{3.22}$$

$$\sum_{r\in\mathscr{R}}\sum_{t\in\mathscr{T}} a_{ir}\lambda^s_{rt} \leq x_i,\ \forall i \in \mathscr{N}^c,\ \forall s \in S, \tag{3.23}$$

$$y_{rt} - \lambda^s_{rt} \leq w^s_{rt},\ \forall r \in \mathscr{R},\ \forall t \in \mathscr{T},\ \forall s \in S, \tag{3.24}$$

$$\lambda^s_{rt} \in \{0,1\},\ \forall r \in \mathscr{R}, t \in \mathscr{T},\ \forall s \in S, \tag{3.25}$$

$$w^s_{rt} \in \{0,1\},\ \forall r \in \mathscr{R}, t \in \mathscr{T},\ \forall s \in S. \tag{3.26}$$

The objective function (3.14) maximizes the total expected profit, prize collected at the selected locations minus the cost of selecting the location, the routing cost and the adjustment of the routing costs after the realization. Constraint (3.15) imposes the budget available for the deployment during the planning horizon. Constraints (3.16) ensure that the number of routes selected during each time period before the uncertainty revelation does not exceed the available vehicles. Constraints (3.17) impose that only the selected locations are covered and are covered only once before the uncertainty revelation. The first stage variable domains are dictated by constraints (3.18) and (3.19).

On the second stage, the objective function (3.20) maximizes the expected prize collected minus the routing costs and penalties incurred. Constraints (3.21) ensure that the budget is respected even if the routing decisions are changed. Constraints (3.22) impose the available number of mobile clinics. Constraints (3.23) ensure that only locations selected on the first stage are covered and that they are covered only once. Constraints (3.24) identifies routes that were selected on the first stage but at the second stage are not selected. Finally, constraints (3.25) and (3.26) impose the domain of the binary variables.

Full Network Recourse

The full network recourse is equivalent to the Routing on First and Second Stage model without any additional constraints (Equations **3.14 - 3.26**)

Simple Recourse

The simple recourse policy (i.e., "observe and pay") can be implemented using the model for the route in the first and second stages by adding a constraint. Hence, it can be modified as follows for the simple recourse policy:

Equations **3.14 - 3.26**

$$\lambda_{rt}^{s} \leq y_{rt},\ \forall r \in \mathscr{R},\ \forall t \in \mathscr{T},\ \forall s \in S, \tag{3.27}$$

Constraints (3.27) restricts the selected routes on the second stage to those previously selected on the first stage.

Reoptimization per time period

One of the recourse policies is to allow the selection of different routes without altering the schedule of visits for the location. This can only be done by allowing the model to select different routes as long as the locations visited at a time period $t \in \mathscr{T}$ remained visited at said time periods. The model for route on first and second stage can be written as follows to allow reoptimization of routes that do not alter the time period it is scheduled for:

Equations **3.14 - 3.26**

$$\sum_{r\in\mathscr{R}} a_{ir}\lambda_{rt}^{s} \leq \sum_{r\in\mathscr{R}} a_{ir}y_{rt},\ \forall i \in \mathscr{N}^{c},\ \forall t \in \mathscr{T},\ \forall s \in S \tag{3.28}$$

Constraints (3.28) impose that only routes containing the locations to be visited on that time period as defined in the first stage can be selected for each time period.

3.4 Solution Method

In this section, we detail our solution methodology for the SBCP modeled as a two-stage stochastic program. First, all the feasible routes are identified using the route generation algorithm described in Section 3.4.1. Our proposed methodology uses scenarios to represent the possible realizations of the uncertain parameters. By using scenarios we aim to optimize not only the cost of tactical plan but also the expected cost of plan adjustments following information updates, represented by distributions based on expert's knowledge. Empirical distributions are used to generate multiple scenarios that contain different values in the random parameters yielding different networks per time period along the planning horizon that are then fed to the two-stage stochastic models to solve the SBCP. Figure 3.7 presents step-by-step our solution approach and these steps are detailed in the following sections.

3.4.1 Route Generation Algorithm

At the planning moment information is available on the expected travel time through the network. Each path segment connecting locations and the depot is identified and the travel times are recorded. A distance matrix is built containing the shortest distances

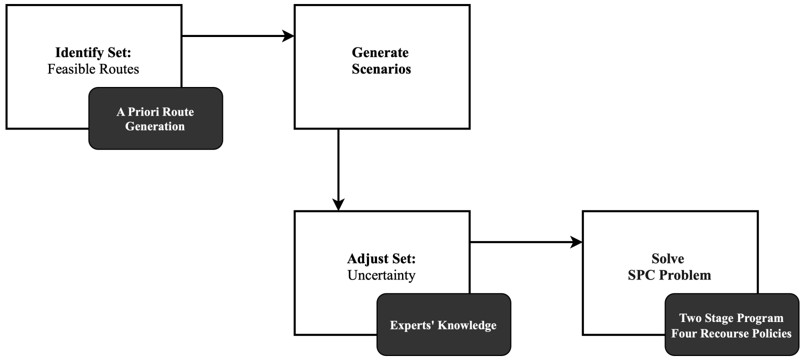


Figure 3.7: Step-by-Step Solution Approach

among all locations and the depot in the network. Algorithm 1 describes the generation of the feasible routes.

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

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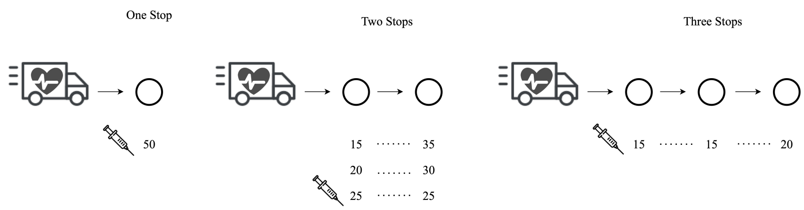
Require: $\mathscr{N}^c, \mathscr{A}, d_{ij}, \theta, \gamma, \delta$

Define $\mathscr{N}_r$ as set of stops (depots and visited locations) in route $r \in \mathscr{R}$
Define $\mathscr{A}_r$ as set of arcs in route $r \in \mathscr{R}$
Define T_r as the total duration of route $r \in \mathscr{R}$
Define c_r as the cost per route $r \in \mathscr{R}$
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 locations that can be visited in a route
Define Q as the capacity per route $r \in \mathscr{R}$
Initialize $N_r \leftarrow 0, T_r \leftarrow 0, c_r \leftarrow 0$
Initialize $a_{ir} \leftarrow 0, i \in \mathscr{N}^e \cup \mathscr{N}^c$
Initialize $G_{ir} \leftarrow 0, i \in \mathscr{N}^c$
Initialize $\bar{\nu} \leftarrow \lfloor (\delta - Q\gamma)/\theta \rfloor$
for $i_0 \in \mathscr{N}^c$ **do**
  for $\nu = 0$ to $\bar{\nu}$ **do**
    Generate all possible routes r
    $\mathscr{N}_r = ((i_0, i_1, ..., i_{\bar{\nu}}, i_0)), i_1, ..., i_{\bar{\nu}} \in \mathscr{N}^c, i_k \neq i_l (1 \leq k \leq \nu, 1 \leq l \leq \nu), \nu = |N_r| - 2$
    $\mathscr{A}_r = \{(i_1, i_2), (i_\nu, i_n)\} \cup \{(i_k, i_{k+1})$ s.t. $1 \leq k \leq \nu\}$
    $a_{ir} = 1, i \in N_r$
    $T_r = \theta(|\mathscr{N}_r| - 2) + 50\gamma + \sum_{(i,j) \in \mathscr{A}_r} \psi d_{ij}$
    $c_r = \sum_{(i,j) \in \mathscr{A}_r} \kappa d_{ij}$
    if $T_r \leq \delta$ **then**
      $\mathscr{R} \leftarrow r$
    end if
  end for
end for

First, the characteristics of the network are provided to the algorithm. These include the number of locations, the arcs connecting locations to locations and to the depot, the time distance on each arc, maximal travel time δ, service time per location (γ), and the setup time at each location θ. With this information we proceed to calculate the maximum number of locations per route $\bar{v}$, which is later used to define the ordered vector of routes. Then all possible routes starting at the depot i_0 are generated. If the route r respects the maximal travel time δ then it is included in the set of routes $\mathscr{R}$.

When visiting more than one location with one route, the total capacity of the mobile clinic must be distributed among the number of stops in a route. Based on conversations with practitioners we have learned that mobile clinic routes can at most visit four different locations in a given day. However, the maximum number of beneficiaries a mobile clinic can serve must be considered when dividing the capacity of the mobile clinics among multiple locations to ensure it justifies the cost in terms of benefit. Therefore, in this study, we only evaluate routes that contain at most the maximum number stops. In order to determine how many individuals would be serviced at each stop in the route we define batch sizes. By defining a minimum number of beneficiaries to serve per location, for this study we use fifteen, then the different possible combinations per stop in a route can be enumerated with increments of five beneficiaries. In this study we arbitrarily selected five as the increment and fifteen as the minimum based on previous exchanges with practitioners. These combinations are then used to identify the number of copies representing the permutations of each feasible route after the feasible routes have been identified by the routing algorithm. This is done by generating copies of feasible routes containing the batch size information (i.e., one copy per batch). Figure 3.8 illustrates an example of batch sizes for a fleet that has a capacity of 50 people served. Note that in this example a feasible route will have only one copy if it contains one stop, five if it contains two stops, and three if it contains three stops. This logic can then be used to copy the feasible routes as per the capacity of the mobile clinics.

Figure 3.8: Batch Size Combinations per Stops in Route



3.4.2 Uncertainty Revelation on Routes

We study the effects of three levels of severity of amplitude in the variations of the uncertain parameters and the performance of four recourse policies. New information is obtained shortly before the next application period, and this information is used to update the tactical plan before the execution. The information concerns the variations of travel time, accessibility, and usability. The uncertainty (i.e., travel time, accessibility, and usability) can be captured with the time parameter describing each route. After identifying all the feasible routes with expected attribute values, the time parameter can be increased to reflect the experts' new information. For instance, the updated estimates of travel times between locations are used to recalculate the total travel time of the route after the revelation of the new information. Any route that violates the maximal travel time δ after the revelation is no longer feasible in the scenario $\mathscr{R}^s$, and therefore it is no longer part of the set of routes. On the other hand, if a route contains a location that is no longer accessible, that route is also eliminated from the set of feasible routes in that scenario. Moreover, routes that contain paths that are no longer usable are also eliminated from the set of feasible routes for that given scenario. Hence, any affected route will no longer be included in the set of routes for the corresponding scenario if the revelation of new updated information results in an unacceptable increase in travel time, an unusable path, or an inaccessible location. The following section explains how the uncertainty is captured in the mathematical models based on practices and observations of field practitioners.

3.4.3 Uncertainty Modeling

This study concentrates on the effects of uncertainty in the network. In the context studied, the demand and location of communities are known (i.e., deterministic). As it is assumed based on field practices that the communities in need of healthcare will not be displaced and the location at which the clinics will offer healthcare services will not vary per community. There is a need for tools that do not require deep analysis from practitioners and that instead rely on data gathered from the field (Liberatore et al., 2013). Hence, we translate experts' knowledge into three levels of severity: mild, moderate, and severe. Because locations are either accessible or not accessible, scenarios are generated with most likely accessibility of 90%, 75%, and 4% for mild, moderate, and severe levels respectively. For travel time increase we consider a percentage range increase in travel time, which means that the parameters of routes are updated using the percentage increase corresponding to each severity case. Individual arcs, e.g., (i_1, i_2), are affected by the travel time increases and this is reflected on the total travel time of the route as a route is a collection of arcs, i.e., $(i_1, i_2, ..., i_{n-1}, i_n)$. The probability of occurrence indicates what percentage of the network is affected by the increase. Similarly, usability is also characterized by a percentage increase and probability of occurrence (i.e., not accessing a location), 2.5%, 5%, and 15% for mild, moderate, and severe levels respectively. The percentage and probability of occurrence for each severity level that characterizes the amplitude of variation on the travel time and usability are presented in Table 3.1. These statistics were identified by preliminary tests conducted and input gather from practitioners.

Table 3.1: Distribution of Severity Levels on Travel Times

	Time Increase			**Probability**		
	Mild	**Moderate**	Severe	Mild	**Moderate**	**Severe**
No Increase	0%	0%	0%	0.75	0.5	0.25
Minimum	1-3%	5-8%	0-20%	0.05	0.125	0.1
Most Likely	3-4%	8-10%	20-50%	0.125	0.2	0.4
Maximum	4-5%	10-15%	50-100%	0.05	0.125	0.1
Usability	∞	∞	∞	0.025	0.05	0.15

We use a random seed to to apply the amplitude in the variations of the uncertain parameters on the set of routes for accessibility of locations, travel times, and usability of roads per severity level (i.e., mild, moderate, and severe) to generate a set of scenarios corresponding to each amplitude of variation. The decisions taken by the model will depend on uncertain parameters; accessibility of locations, travel times, and usability of the roads.

3.5 Computational Results

In this section, we detail how we test the proposed methodology and we present and discuss the results. First, we provide descriptive statistics for the cases extracted from real data. Then, we discuss the in-sample and out-of-sample stability of the scenario generation. Afterward, we present the key performance indicators used in the analysis. Finally, we present and discuss the results. The solution algorithm was implemented in C++ and the mathematical programs were solved by CPLEX 22.1.0 on an Intel E5-2683 v4 VMware virtual machine with eight cores Broadwell CPUs at 2.1Ghz, and 32 GB of vRAM on Linux operating system.

3.5.1 Networks

To test our proposed methodology we use data from one real-life mobile clinic deployment in Iraq shared by Première Urgence Internationale, an international nongovernmental organization. We also use two additional cases derived from real-life data available at the humanitarian data exchange (HDX) for the countries of Malawi and Kenya (HDX, 2021). The three cases have network structures that vary in typologies and number of communities (see Figure 3.9). In order of the largest to the smallest number of communities, we test our algorithm on the cases of Iraq, Kenya, and Malawi. Descriptive statistics, minimal (Min), maximal (Max), average (Average), and standard deviation (St. dev.), on population and road distances between locations are presented in Table 3.2. Note that each network has a different topology. Iraq is the largest network in terms of the radius of the deployment region and as well as the more sparse between the two large networks.

Iraq is in a rural setting with longer and fewer road segments compared to the other cases. On the other hand, Kenya represents a smaller case with fewer locations. Yet, when you compare Kenya to Malawi although they are both smaller in terms of the number of locations Malawi has a higher population per location. These differences between the studied networks will allow us to identify the effects of the network topologies on the performance of deployments under uncertainty.

Figure 3.9: Networks

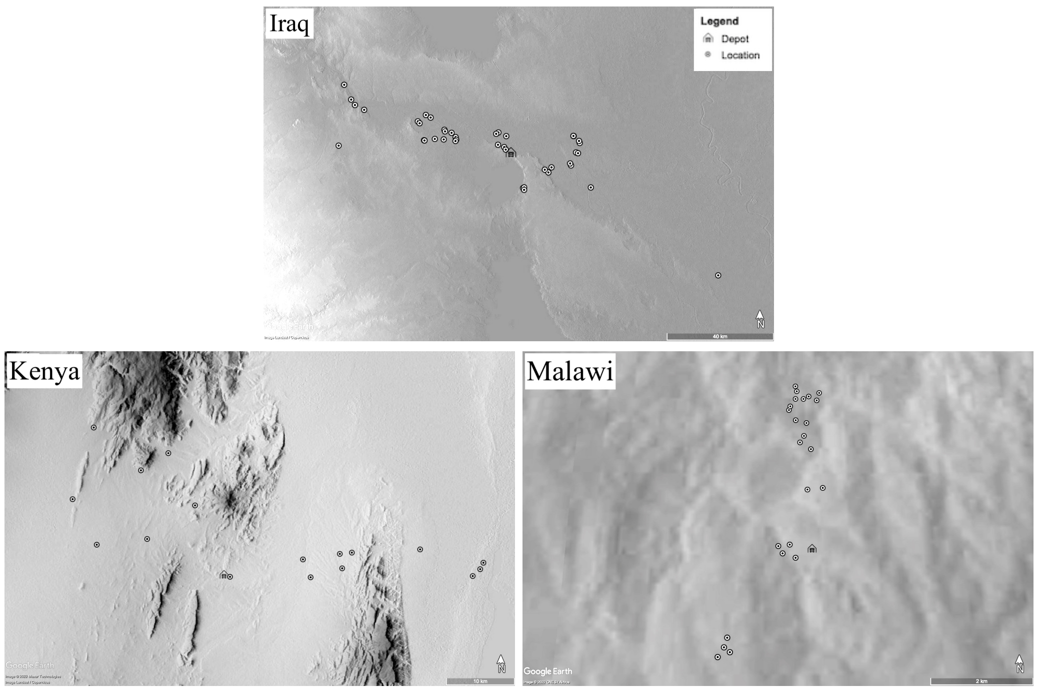


Table 3.2: Descriptive Statistics for the Cases

Country	Locations	Population				Distance (km)			
		Average	Max	Min	St. dev.	Average	Max	Min	St. dev.
Iraq	41	11,770	168,000	1,160	26,700	51.47	194.56	0.11	34.34
Kenya	17	186	860	23	225	65.02	678.89	0.39	143.14
Malawi	24	859	1,800	150	452	3.70	13.00	0.06	2.90

To estimate the prize collected at each location we use the BCR, this tool requires knowing the cost of the deployment in advance. Hence, first we need to calculate the costs of delivering and administering the vaccines. The estimation costs were calculated based on each country's cost of living (Numbeo, 2022). The routing costs per location are obtained by considering routes with only one stop to the specific location. The operational costs (medical personnel, medical equipment, and vaccines) are calculated based on the international humanitarian pay standards, based on Canada' occupational salaries (Canadian Job Bank, 2022). All costs are summed up and distributed among all communities proportionally to the population at each location. Previous studies have found that in the context of vaccinations the cost benefit ratio (BCR) is between 1% and 5% (Okafor and Ekwunife, 2021; Domingo, 1999; Bae et al., 2013; Raj et al., 2019; Hsu et al., 2003; Pathania, 1999) and, hence we test the effects of BCRs ranging from 1% to 5%. The descriptive statistics for the BCR of 1% per person for each country calculated in US dollars are presented in Table 3.3. Among all the countries we can see that the highest BCR per person is in Kenya for $106.72 per person, whereas the lowest BCR is in Malawi for $0.80 per person. This means that in Kenya the benefit of getting vaccinated can amount to up to $106.72. Using the BCR allows for the prize and the costs in the objective function to be both in monetary units.

Table 3.3: BCR of 1% for All Countries (in USD)

Country	**Average**	**Max**	**Min**	**St. Dev**
Iraq	12.06	26.68	2.07	9.34
Kenya	14.08	106.72	8.27	8.24
Malawi	2.28	8.79	0.80	1.75

3.5.2 Stability Analyses

In this section we conduct tests to analyze the stability of the scenario generation. According to Kaut and Stein (2003), a scenario-generation method must have have stability, as they represent possible realizations. In this paper, the distribution of the stochastic parameters (i.e., access to locations, usability of roads, and travel times) are approximated by discrete distributions with a limited number of outcomes commonly referred to in the literature as scenarios or scenario trees (Kaut and Stein, 2003). Hence, we study the impact of the scenarios on the performance of the model. The larger the set of scenarios the better the representation of the realizations and at the same time the more difficult it is to obtain optimal solutions (Wang et al., 2019). Furthermore, the objective function of the models may take different values on each set of scenarios and, therefore if the procedure is rerun on a different scenario the objective function will be different. Hence, with our stability analyses we seek to verify that our scenarios and the number of scenarios accurately represent the problem.

To test the in-sample stability, we solve our four two-stage models for each of the three different levels of uncertainty using 15 different random seeds to generate scenario sets. We calculate the average and standard deviation on the obtained objective functions as well as the error percentage. This is repeated for different numbers of scenarios in increments of ten until reaching an acceptable error Kaut and Stein (2003). Table 3.4 presents the results obtained using the network of Kenya.

Table 3.4: In Sample Stability Tests

		Scenarios											
		10			**20**			**30**			**40**		
	Recourse Policies	Avg. Obj. Function	Std. Dev.	Error	Avg. Obj. Function	Std. Dev.	Error	Avg. Obj. Function	Std. Dev.	Error	Avg. Obj. Function	Std. Dev.	Error
Mild	Full Recourse	50,375.96	162.51	1.4%	50,176.32	262.73	1.9%	49,789.51	129.15	0.9%	49,714.37	129.60	0.9%
	Reoptimize per Time Period	49,092.49	694.07	6.4%	48,434.14	961.91	7.9%	47,059.68	548.86	3.8%	46,730.54	570.69	3.7%
	Simple Recourse	49,060.39	698.00	6.4%	48,394.86	972.10	7.9%	46,984.35	595.38	4.0%	46,664.24	586.16	3.9%
	Route on Second Stage	50,823.60	0.00	0.0%	50,823.60	0.00	0.0%	50,823.60	0.00	0.0%	50,823.60	0.00	0.0%
Moderate	Full Recourse	48,438.15	439.94	3.3%	48,189.37	441.68	3.3%	47,708.68	203.96	1.2%	47,576.71	202.69	1.4%
	Reoptimize per Time Period	42,000.05	1,031.27	10.2%	40,976.69	1,451.13	12.9%	38,869.05	767.88	7.4%	38,193.25	765.64	7.0%
	Simple Recourse	41,546.95	1,281.78	12.7%	40,550.51	1,576.53	14.0%	38,424.97	876.45	8.7%	37,865.46	771.16	7.6%
	Route on Second Stage	50,761.31	140.24	0.8%	50,755.78	118.34	0.8%	50,724.37	81.03	0.5%	50,700.49	88.32	0.6%
Severe	Full Recourse	35,149.79	1,520.24	13.7%	34,911.20	1,291.14	13.7%	34,320.53	650.11	6.6%	34,062.67	630.09	5.9%
	Reoptimize per Time Period	21,335.54	1,300.54	19.0%	20,044.54	1,712.83	28.2%	17,608.04	789.01	12.6%	16,885.32	562.30	10.2%
	Simple Recourse	19,919.48	1,330.19	20.2%	18,747.42	1,693.13	29.3%	16,418.71	811.02	13.9%	15,669.11	589.18	11.4%
	Route on Second Stage	40,608.32	1,891.94	15.0%	40,518.81	1,555.94	15.0%	40,204.33	791.30	7.0%	40,056.39	768.62	6.2%

Using the results of the in-sample stability in Table 3.4 for the network of Kenya we can extrapolate the required number of scenarios for each of the four models under each of the three uncertainties. It can be observed that ten scenarios provide an error below 10% for all policies under mild uncertainty. Under moderate uncertainty, all policies reach an acceptable error below 10% with only 30 scenarios. However, under severe uncertainty, the full recourse and route on second stage policies reach errors below 10 % with 40 scenarios. This means that for reoptimize per time period and simple recourse more than 40 scenarios are needed to reach stability with an error below ten percent. Both the full recourse and the route on second stage reach stability under all levels with only 30 scenarios. One can infer that solving the models with a set of 40 scenarios can provide sufficient in-sample stability for the cases under all levels of amplitude variations in the uncertain parameters and, therefore the numerical analysis that follows can be conducted with sets of 40 scenarios. Additionally, we used a set of 1,000 scenarios to represent the "true"problem and test the *out-of-sample stability* of our model. The *out-of-sample* test ensures that the solutions found using a sample of the reality (i.e., a scenario set) do not deviate in performance when applied in reality, for practical reasons a bigger scenario set is used to test this (Kaut and Stein, 2003). Tests resulted in an error of less than eight percent between the highest and lowest values. Hence, the scenario generation method used in this study does comply with the in-sample and out-of-sample reliability requirements.

3.5.3 Performance Indicators

We propose three relevant performance indicators to analyze the results obtained with the proposed methodology. The value of the objective function or the total profit of the solutions (i.e., prize minus cost) is used as a performance indicator as we want to maximize the benefit offered by mobile clinic deployment. Additionally, the number of communities selected in the first stage and covered in the second stage can also provide insights as to how much of the original plan can be fulfilled. These performance indicators will be used to compare the different recourse policies when subjected to the levels of uncertainty. Also, they will be used to analyze the sensitivity to different networks (i.e., cases: Iraq, Kenya, and Malawi) and to the BCRs (i.e., 1% to 5%).

3.5.4 Analyses and Managerial Insights

In this section we present the results from the sensitivity analysis for the three levels of uncertainty: mild, moderate, and severe. We also discuss how the uncertainty levels affect the deployment of mobile clinics. Moreover, we study the impact of the BCR percentage (1%-5%) on the solutions obtained. Finally, we compare the recourse policies in terms of flexibility and reliability. For the numerical results presented, each model (i.e., recourse policy) is tested on fifteen different instances for each network at each of the three severity levels. Hence, the model is executed 180 times per network (i.e., 15x3x4) with a set of 40 scenarios for each level of amplitude variation. Therefore, we present the results as averages of the cost, benefit, and objective function (i.e, benefit minus cost). For the analyses, we use the network of Kenya with a BCR of five percent as our *base case* instance. The base case instance is used to derive managerial insights into the impact of decisions in the performance of the deployment.

Severity Levels

In this study, we explore the performance of the proposed methodology on three different levels of uncertainty. Where each level represents a different amplitude of variation in the uncertain parameters (See Section 3.4.3). In Tables 3.5 through 3.7 we present the average benefit, average cost, and average value of the objective function (i.e., profit) for the cases of Kenya, Iraq, and Malawi.

Table 3.5: Performance of the Policies Under the Severity Levels: Kenya

		Avg. Prize	Avg Cost	Avg. of Obj Function
	Deterministic	51,508.00	684.32	50,823.60
Full Recourse	Mild	42,149.83	196.80	49,714.37
	Moderate	42,843.11	185.21	47,576.71
	Severe	34,811.11	224.36	34,062.67
Reoptimize per Time Period	Mild	46,329.85	202.80	46,730.54
	Moderate	38,744.30	267.35	38,193.25
	Severe	16,988.13	457.81	16,885.32
Simple Recourse	Mild	41,370.73	207.71	46,664.24
	Moderate	36,739.06	232.53	37,865.46
	Severe	16,198.96	310.13	15,669.11
Route on Second Stage	Mild	51,508.00	155.69	50,823.60
	Moderate	51,420.69	192.62	50,700.49
	Severe	41,202.15	237.43	40,056.39

We can observe that the highest profit attainable, dictated by the deterministic model, can be reached with the route on second stage policy under mild uncertainty in all cases. However, when we compare the costs of the deterministic model and the route on second stage policy we can see a higher cost is incurred when using the deterministic deployment plan. This notable difference in cost can be attributed to the number of locations visited. Hence, with the route on second stage we would service more communities, which in

Table 3.6: Performance of the Policies Under the Severity Levels: Iraq

		Avg. Prize	Avg Cost	Avg. of Obj Function
	Deterministic	117,134.00	2,450.40	114,684.00
Full Recourse	Mild	115,153.43	85.76	114,453.60
	Moderate	109,729.97	113.95	111,827.33
	Severe	102,076.55	243.52	99,995.95
Reoptimize per Time Period	Mild	115,924.33	99.05	113,883.53
	Moderate	104,310.33	347.40	102,007.53
	Severe	66,246.00	912.05	65,111.77
Simple Recourse	Mild	110,494.19	129.93	113,658.27
	Moderate	10,364.16	145.54	20,519.20
	Severe	60,373.81	668.43	62,634.29
Route on Second Stage	Mild	117,134.00	69.60	114,684.00
	Moderate	117,060.00	76.36	114,605.47
	Severe	112,451.67	252.89	109,932.60

Table 3.7: Performance of the Policies Under the Severity Levels: Malawi

		Avg. Prize	Avg Cost	Avg. of Obj Function
	Deterministic	9,199.89	466.90	8,732.99
Full Recourse	Mild	8,071.40	378.93	8,563.64
	Moderate	8,237.30	370.87	8,252.39
	Severe	7,714.07	465.83	7,167.95
Reoptimize per Time Period	Mild	8,616.35	410.58	8,120.73
	Moderate	7,392.03	498.46	6,815.28
	Severe	4,910.84	778.00	4,158.21
Simple Recourse	Mild	3,034.69	218.09	4,892.44
	Moderate	1,491.66	270.76	4,981.13
	Severe	4,241.21	399.27	3,800.48
Route on Second Stage	Mild	9,199.89	373.10	8,732.99
	Moderate	9,187.14	375.92	8,717.47
	Severe	8,773.32	476.25	8,207.97

turn increases the prizes, while in a system without uncertainty the model will opt to visit locations with a higher benefit and at a lower cost. Route on second stage also is the highest performing policy in terms of profit under moderate and severe conditions. This indicates that selecting the communities before the information is updated and later deciding on the time period to schedule visits and routes, once an update is received, would allow practitioners to offer the maximum benefit. Reoptimize per time period outperforms the full recourse policy under mild conditions but the opposite is true under moderate and severe conditions for all cases. Not surprisingly, simple recourse policy provides the smallest profit under all uncertainty levels. These observations apply to all three cases studied, which indicates that the network on which the deployments take place does not impact the performance of the policies under different levels of amplitude variation in the uncertain parameters.

We also observe that a route on second stage policy provides practitioners the maximum benefit collection at the minimum cost. Yet, this policy while it does offer flexibility it does not offer a reliable plan to be shared with the beneficiaries. If a priority of the deployment is to provide beneficiaries with a reliable schedule, practitioners should then opt for the Reoptimize per time period policy under mild, moderate conditions. However, practitioners must consider that a Reoptimize per time period, as well as a simple recourse policy, can be detrimental to the impact of the deployments, in which case a more flexible policy such as Route on second stage will prove to be more effective.

Benefit Cost Ratio

In this section, we study the sensibility of the model to different BCRs. We tested BCRs under all three uncertainty conditions and present the number of communities serviced (i.e., visited after the information is updated) per each recourse policy proposed for each case (See Tables 3.8, 3.10, and 3.9).

Table 3.8: Policies' Sensitivity to BCR: Kenya

		Full Recourse	Reoptimize per Time Period	Simple Recourse	Route on Second Stage
Mild	BCR1	10	10	10	10
	BCR2	10	10	10	10
	BCR3	10	10	10	10
	BCR4	10	11	10	10
	BCR5	10	11	10	10
Moderate	BCR1	10	11	10	10
	BCR2	10	10	10	10
	BCR3	10	11	10	11
	BCR4	10	12	10	11
	BCR5	10	12	10	11
Severe	BCR1	14	11	10	14
	BCR2	15	15	10	16
	BCR3	15	11	10	16
	BCR4	16	16	10	16
	BCR5	16	16	10	16

Table 3.9: Policies' Sensitivity to BCR: Malawi

		Full Recourse	Reoptimize per Time Period	Simple Recourse	Route on Second Stage
Mild	BCR1	10	10	10	10
	BCR2	10	10	9	10
	BCR3	10	10	9	10
	BCR4	10	11	7	10
	BCR5	10	11	5	10
Moderate	BCR1	10	10	9	10
	BCR2	10	11	9	10
	BCR3	10	12	8	10
	BCR4	10	12	7	10
	BCR5	10	13	7	10
Severe	BCR1	10	10	9	11
	BCR2	12	12	9	12
	BCR3	10	12	8	12
	BCR4	10	17	7	12
	BCR5	10	17	7	12

Table 3.10: Policies' Sensitivity to BCR: Iraq

		Full Recourse	Reoptimize per Time Period	Simple Recourse	Route on Second Stage
Mild	BCR1	30	30	25	29
	BCR2	30	29	16	29
	BCR3	30	30	16	30
	BCR4	30	30	15	15
	BCR5	29	31	16	29
Moderate	BCR1	30	30	14	29
	BCR2	30	32	7	29
	BCR3	30	34	5	30
	BCR4	30	35	5	30
	BCR5	30	35	3	30
Severe	BCR1	31	33	29	31
	BCR2	31	36	29	31
	BCR3	32	39	30	33
	BCR4	32	40	29	32
	BCR5	32	40	29	33

From Table 3.8 we can observe that the simple recourse policy is not sensible to the BCR under any of the severity levels for the case of Kenya as it always services 10 communities. However, for the cases of Malawi and Iraq we can see that the simple recourse is sensible to the BCR. One explanation for this distinction may be the different BCR per country with Kenya having the highest among the three cases. We can observe that the full recourse is sensitive to the BCR under severe conditions only. Policies that are sensitive to the BCR tend to increase the number of communities visited as the BCR and severity increase for all cases. This is not surprising as the maximization of the profit will be higher at higher BCR percentages. Furthermore, we present the average objective function (i.e., profit), average total cost, and average total prize as well as the average number of communities in Tables 3.11 to 3.13.

Table 3.11: Sensitivity to Batch Size and BCR: Kenya

	Avg. Obj Function	Avg. Total Cost	Avg. Prize	Avg. No. Locations
BCR1	7,519.03	289.78	7,883.46	10.85
BCR2	15,733.33	278.50	15,792.74	11.37
BCR3	23,735.57	272.64	23,575.24	11.48
BCR4	32,212.77	273.16	31,732.46	11.62
BCR5	40,443.52	273.44	39,370.30	11.71
No Batch Size	64,057.97	306.13	60,515.50	16.22

We can observe that the maximum profit can be obtained with the highest BCR at five percent, when we consider a batch size. This is expected as the prize collected would be higher and the cost incurred per BCR is stable among all five percentages. Now when we do not consider the batch size on the route we reach an even higher profit, even if the

Table 3.12: Sensitivity to Batch Size and BCR: Iraq

	Avg. Obj Function	Avg. Total Cost	Avg. Prize	Avg. No. Locations
BCR1	18,594.93	429.00	20,212.12	30
BCR2	38,162.57	423.33	39,446.06	30
BCR3	57,780.08	426.81	58,725.93	30
BCR4	77,807.97	432.91	78,009.73	30
BCR5	96,769.04	430.38	96,804.03	30
No Batch Size	141,578.09	918.78	139,642.04	38

Table 3.13: Sensitivity to Batch Size and BCR: Malawi

	Avg. Obj Function	Avg. Total Cost	Avg. Prize	Avg. No. Locations
BCR1	1,097.79	388.18	1,470.84	10
BCR2	2,662.14	404.05	2,933.28	10
BCR3	4,168.90	415.36	4,301.39	11
BCR4	5,577.29	415.72	5,596.54	11
BCR5	7,011.05	421.77	6,928.44	11
No Batch Size	13,169.21	842.28	13,572.57	21

cost increases. Note that not considering the batch size implies that the location's full prize can be collected in a single visit. Hence, this can be explain the higher profit. This represents a reality in which mobile clinics may administer and also leave vaccines for a trained member of the community to administer them. Using this practice practitioners may have a higher positive impact on the communities that would justify the additional routing costs.

Flexibility and Reliability

When deploying mobile clinics in humanitarian contexts both flexibility and reliability are important aspects. Flexibility allows practitioners to ensure the efficient and effective utilization of resources allocated to the deployment. On the other hand, reliability can provide an incentive for populations to seek healthcare offered by mobile clinics (Du Mortier and Coninx, 2007a). In this section we study the flexibility and reliability offered by the different policies based on the locations visited (See Tables 3.14, 3.15, and 3.16). Also, we analyze how the profit collected per recourse policy is affected based on Tables 3.5 through 3.7.

From Tables 3.14, 3.15, and 3.16 it can be observed that under severe conditions all policies resort to visit a higher number of communities. However, we can see that there is

Table 3.14: Number of Locations: First Stage vs. Second Stage for Kenya

	Full Recourse			Reoptimize per Time Period			Simple Recourse			Route on Second Stage			Deterministic
	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	Visited
Mild	11	9	2	12	10	1	11	8	3	11	11	0	11
Moderate	11	10	1	12	9	4	11	8	3	12	11	1	−−
Severe	15	11	5	15	5	10	10	3	7	16	11	5	−−

Table 3.15: Number of Locations: First Stage vs. Second Stage for Iraq

	Full Recourse			Reoptimize per Time Period			Simple Recourse			Route on Second Stage			Deterministic
	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	Visited
Mild	30	29	1	30	30	0	30	28	2	30	30	0	30
Moderate	30	29	1	32	28	5	14	7	7	30	30	0	–
Severe	32	30	2	38	21	16	30	16	14	33	30	2	–

Table 3.16: Number of Locations: First Stage vs. Second Stage for Malawi

	Full Recourse			Reoptimize per Time Period			Simple Recourse			Route on Second Stage			Deterministic
	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	1st Stage	2nd Stage	Not visited	Visited
Mild	10	9	1	11	10	1	5	3	3	10	10	0	10
Moderate	10	9	0	13	9	4	7	2	5	10	10	0	–
Severe	12	10	2	19	8	11	10	5	5	12	10	2	–

a decline on the number of communities originally selected and the ones serviced for all policies and this difference increases at the highest uncertainty level. If we calculate the differences between selected and serviced communities the route on second stage seems to provide the best flexibility and reliability. However, under severe conditions the full recourse policy outperforms the route on second stage policy. The reoptimized per time period policy seems to be the policy that offers the least reliability. Hence, a simple recourse policy can outperform the reoptimized per time period policy under moderate and severe uncertainty regardless of the network topology.

Tables 3.5 through 3.7 can aid to compare the policies based on the prize collected. It can be observed once more that the route on second stage policy out performs the other policies. The route on second stage policy even reaches the same profit level as the deterministic model under mild and moderate conditions. The full recourse policy appears to be equivalent to the route on second stage policy under mild conditions. When choosing between a route on second stage policy and a full recourse practitioners can opt for the full recourse to provide communities an estimated schedule under mild conditions. Yet, it is more favourable to not have the reliability component and ensure a higher profit when possible and, thus, employ a route on second stage policy under moderate and severe conditions.

3.6 Conclusions

In this study, we have employed an SBC methodology for mobile clinic deployments under uncertainty. We propose four two-stage models, each representing a different adjustment (i.e., recourse policies) to address the uncertainty. Each model that seeks to maximize the total profit collected (i.e., benefit minus cost). Our solution approach is tested on three different cases for vaccination campaigns in humanitarian contexts using real world data.

We tested different levels of uncertainty: mild, moderate, and severe. These levels of uncertainty represent different of amplitudes in variation of the uncertain parameters. With a BCR technique, previously introduced in the vaccination literature, we translate benefit into a monetary prize. The results showed that three out of four models are sensitive to higher BCRs under moderate and severe uncertainty levels. However, the simple recourse policy is not sensitive to different BCR levels. This means that the performance of the simple recourse or a do nothing adjustment plan will not vary based on the scale of the benefit provided. The four policies were compared against the deterministic model to measure their performance and study the impact of accounting for the adjustment costs. In this study, the route on second stage policy outperformed other policies both in profit and locations served. This policy offered the most flexibility to practitioners, however it does not allow for a preliminary schedule to be announced to the communities. To counter this downside, practitioners can opt to instead use a reroute per time period to offer a higher level of reliability while reaching more communities. On the other hand, opting for a simple recourse policy can offers even higher reliability while achieving similar levels as the reroute per time period policy in terms of profit.

The proposed solution approach is only evaluated for a single origin-destination (i.e., depot) as it is pertinent for a mobile clinic deployment context. However, the models are flexible enough to consider routes that can contain different origins and destinations. Future research can build upon the methodology proposed and evaluate if the inclusion of multiple depots affects the solutions obtained.

Conclusions

This thesis is the first to present the tactical planning problem of mobile clinic deployments with a focus on complex emergencies, such as conflict zones. Furthermore, this thesis develops methodology to assist practitioners in the planning decision process of where to deploy (i.e., population points) to achieve continuity and coverage objectives and which routes to take considering explicitly the uncertainty on the transportation network. The thesis aimed to truly capture the reality faced by practitioners and, hence, 60% of the thesis was conducted in collaboration with PUI. Moreover, this thesis is the first to capture continuity and coverage in a healthcare context using a mathematical model and proposing different ways to represent continuity. Also, it is the first to formulate mobile clinic deployments as a multiperiod location routing problem. This thesis is also the first to propose a Stochastic Prize Collection formulation. We are also the first to tackle three network uncertainty parameters at the same time and propose various policies for plan adjustments.

First, we provided an analysis of the current literature and practices on mobile clinic deployments, concentrating on deployments in conflict zones. This analysis was done by combining an integrative literature review and an instrumental case study to identify the challenges and hurdles for practitioners deploying mobile clinics in conflict zones for humanitarian relief. This analysis depicted the decisions entailed in mobile clinic deployments and described how the context of conflict zones, both during and after, presents challenges to practitioners. In part due to the healthcare risks faced by people living in conflict zones or returning to what once was a conflict zone. Moreover, mobile clinic deployments in conflict zones face additional logistical challenges attributed to security risks, economical constraints, and uncertainty during and after conflicts. Furthermore, this analysis showed the dearth of decision support tools for the strategic, tactical, and operational phases of deployments of mobile clinics in all contexts.

The second chapter tackled the deterministic tactical planing of mobile clinics over a planning horizon as an MLRP that reflects the time dependency of mobile clinic operations. The planning tool identifies the frequency of service and the appropriate locations to service while considering the proper utilization of resources. This chapter was developed as a collaboration with PUI a NGO that deploys mobile clinics for humanitarian relief world wide. The methodology developed accounts for the coverage and continuity of healthcare provided to each location. The study presented managerial insights and highlights how the strategical decisions of budget and fleet size impact the performance of the deployment. This study clearly illustrated how practitioners can calibrate the continuity and coverage components to either visit more locations or service more people multiple times. Also, it shows a direct correlation between the resources (i.e., budget and number clinics) on a deployment and the impact of the program (i.e., benefit delivered). Using the proposed multiperiod location-routing method practitioners can also provide concrete evidence to justify the required number of clinics and the minimum budget to achieve the desired outcome in benefit delivery. Moreover, it demonstrates that simplification of parameters such as division of capacity (i.e., how many people are served per location) or inclusion of continuity (i.e., number of times a beneficiary is serviced) will still yield a high performance on the deployment. We also proved that if the information is not available to quantify the continuity benefit, using only the coverage benefit still yields acceptable tactical plans.

Finally, the third chapter studied the impact of three sources of uncertainty faced by practitioners (i.e., accessibility to locations, travel time increase, and usability of roads) and three levels of severity. The deployment of mobile clinics was modeled as a two-stage stochastic program that seeks to maximize the benefit offered. Furthermore, we propose and test four recourse policies reoptimize per time period, route on second stage, simple, and full network recourse policies. Models in this chapter assumed a known a single predefined departure point, selected communities to be served and designed associated routing under uncertainty. The methodology was tested on real world instances from Iraq, Kenya, and Malawi. We document the added value of considering uncertainty in the network in both the cost and the benefit delivery. This study shows that deployments of mobile clinics that take place in areas with severe uncertainty are at a greater risk of under performing (i.e., delivering less benefit to those in need) when compared to those deployed under mild or moderate uncertainty if no recourse policies are in place. Moreover, this study shows the trade-off between flexibility (i.e., ability to change a plan) and reliability (i.e., minimum change on previously disclosed plans). As a result of the analysis out of the four policies the reroute on second stage offers more flexibility allowing a higher benefit to be offered at a lower cost, whereas a simple recourse offers higher reliability by minimizing the alterations or cancellations at the population points. However, we show that reoptimizing per time period offers reliability while being flexible enough to still providing a substantial benefit to the population. Furthermore, we demonstrated that under different levels of uncertainty the best performing recourse policy varies.

Although this study contributes to the literature on mobile clinics and humanitarian relief it is not without its limitations. However, these limitations as well as the contributions open avenues for future research. First of all, the analysis of mobile clinic deployments concentrates on conflict zones. This analysis could be extended to humanitarian relief for various types of disasters and multiple contexts (e.g., complex disasters, pandemic response, prevention campaigns). This applies to both the literature review and the case study. Moreover, the deterministic multiperiod location-routing tool proposed for tactical planning could be improved upon by including other continuity benefit equations. This tool also considers continuity as the number of follow-up visits. However, it would be interesting to study the continuity offered by the same clinic staff (i.e., doctors and nurses) instead of the number of visits by the deployment project. This study did not address said continuity as there was a limited number of medical personnel and clinics. Yet, for a deployment in high density population context that has a vast number of resources (i.e., mobile clinics, medical personnel) it would be imperative to ensure continuity offered by the staff. On the other hand, the stochastic benefit collection methodology could be expanded to other contexts besides vaccination campaigns, such as responses to disasters or primary healthcare delivery after an earthquake or during monsoon season. Moreover, other uncertainty sources, other than those affecting the transportation network, could be included (e.g., demand or capacity). The tool proposed is only evaluated for a single depot network but with the route generation algorithm, it could easily be adapted and tested for a multiple depot context. While we target the most vulnerable villages, both studies lack an equity or fairness component to ensure that no preference is given to big or small villages. This would require a more exhaustive data collection from real cases and perhaps the development of a mechanism to better quantify benefit.

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Appendix A – Chapter 2 Appendix

Summary of the mathematical notation

Table 1 presents a summary of the sets, parameters, and decision variables used in our mathematical model.

Detailed computational results

Table 2 contains the detailed computational results when fixing $m = 5$ and $B = 5,000$ with equal division of 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. Note that when $\beta_i = 0$ and with constant marginal CNT benefits, the obtained solution represents the one implemented by our partner (the *base case*). 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 3 contains the detailed computational results when fixing $m = 5$ and $B = 5,000$ with constant marginal CNT benefits for *population proportion*, *score proportion*, *vulner-*

ability proportion, and *accessibility proportion*. Note that the results for *equal proportion* have been presented in Table 2. 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 4 contains the detailed computational results when fixing $m = 5$ and $B = 5,000$ 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 1: Mathematical Notation

Sets	
$\mathscr{N}^e$	Set of depots
$\mathscr{N}^c$	Set of villages to cover
$\mathscr{A}$	Set of arcs
$\mathscr{V}$	Set of visit frequencies (number of times a patient may be served)
$\mathscr{T}$	Set of successive time periods
$\mathscr{R}$	Set of feasible routes
$\mathscr{R}^t$	Set of feasible routes at time period $t \in \mathscr{T}$
Parameters	
p_i	Population at village $i \in \mathscr{N}^c$
c_i	Fixed cost of operating a depot $i \in \mathscr{N}^e$ or serving patients at a village $i \in \mathscr{N}^c$
β_i	Coverage benefit (COV benefit) associated with covering village $i \in \mathscr{N}^c$
β_i^v	Continuity benefit (CNT benefit) associated with serving a patient at village $i \in \mathscr{N}^c$ exactly $v \in \mathscr{V}$ times
d_{ij}	Distance of arc $(i, j) \in \mathscr{A}$
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 $r \in \mathscr{R}$ visits node $i \in \mathscr{N}^e \cup \mathscr{N}^c$, zero otherwise
θ	Setup time at village $i \in \mathscr{N}^c$
γ	Time to serve a patient
δ	Maximum duration of a route
G_{ir}	Patients served at location $i \in \mathscr{N}^c$ with route $r \in \mathscr{R}$
c_r	Transportation costs of route $r \in \mathscr{R}$
Decision Variables	
x_i	Binary variable equal to one if village $i \in \mathscr{N}^c$ is covered, zero otherwise
y_i	Binary variable equal to one if depot $i \in \mathscr{N}^e$ is selected, zero otherwise
λ_r^t	Binary variable equal to one if route $r \in \mathscr{R}^t, \forall t \in \mathscr{T}$, is selected, zero otherwise
ω_i^v	Binary variable equal to one if all the population at location $i \in \mathscr{N}^c$ 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 $i \in \mathscr{N}^c$ at least v times

Table 2: 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 3: 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

Table 4: 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

Route generation algorithm

Algorithm 1 details how the set of routes is generated a priori as input for mobile clinic deployment. First, we provide the information needed for the algorithm to generate the 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 define the maximum number of villages that can be visited in a route as

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

which is computed as the 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 ($\theta > 0$). Note that when $\theta = 0$, then we can defined

$$\bar{v} = \min \left\{ 50, |\mathscr{N}^c|, \left\lfloor (\delta - 50\gamma) / \left(\min_{(i,j) \in \mathscr{A}, i \neq j} \psi d_{ij} \right) \right\rfloor \right\}$$

as the minimum between 50 (i.e., if we visit one patient per village), the total number of villages, and a lower bound on the potential number of covered villages according to the total time remaining for travel (and setup) and the minimum travel time (ψ is defined as the time in minutes per unit of distance). Then, we generate all possible routes r that start at depot $e_1 \in \mathscr{N}^e$ and end at depot $e_2 \in \mathscr{N}^e$ (lines 12–27). The sets of each route are initialized and its 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 distance. The number of patients served at each location is computed according the different rules proposed in Section 2.4.4. 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 $\mathscr{R}$ (lines 22–23).

Algorithm 2 Generation of the Set $\mathscr{R}$ of Feasible routes

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

Define $\mathscr{N}_r$ as set of stops (depots and covered villages) in route $r \in \mathscr{R}$
Define $\mathscr{A}_r$ as set of arcs in route $r \in \mathscr{R}$
Define T_r as the total duration of route $r \in \mathscr{R}$
Define c_r as the cost per route $r \in \mathscr{R}$
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 $a_{ir} \leftarrow 0, i \in \mathscr{N}^e \cup \mathscr{N}^c$
Initialize $G_{ir} \leftarrow 0, i \in \mathscr{N}^c$
Initialize $\bar{\nu} \leftarrow \lfloor(\delta - 50\gamma)/\theta\rfloor$
for $e_1 \in \mathscr{N}^e$ **do**
    for $e_2 \in \mathscr{N}^e$ **do**
        for $\nu = 0$ to $\bar{\nu}$ **do**
            Generate all possible routes r
            $\mathscr{N}_r = (e_1, i_1, ..., i_\nu, e_2), i_1, ..., i_\nu \in \mathscr{N}^c, i_k \neq i_l (1 \leq k \leq \nu, 1 \leq l \leq \nu), \nu = |N_r| - 2$
            $\mathscr{A}_r = \{(e_1, i_1), (i_\nu, e_2)\} \cup \{(i_k, i_{k+1})$ s.t. $1 \leq k \leq \nu\}$
            $a_{ir} = 1, i \in N_r$
            $T_r = \theta(|\mathscr{N}_r| - 2) + 50\gamma + \sum_{(i,j)\in\mathscr{A}_r} \psi d_{ij}$
            $c_r = \sum_{(i,j)\in\mathscr{A}_r} \kappa d_{ij}$
            Compute $G_{ir}, i \in \mathscr{N}_r \cap \mathscr{N}^c$ according to capacity division (see Section 2.4.4)
            if $T_r \leq \delta$ **then**
                $\mathscr{R} \leftarrow r$
            end if
        end for
    end for
end for