ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor Thesis BSc^2 in Econometrics and Economics

Health Care for Refugees in Transit: Multi-Period Mobile Facility Location Problem with Mobile Demand

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June 29, 2022

Abstract

Refugees in transit are at high risk of health problems due to bad living standards and limited access to health care. To increase the health of refugees, regular and preventative health care needs to be offered to refugees in transit. Mobile health clinics can be used to provide health care at different locations along refugee routes. This paper therefore determines the most efficient path of mobile health clinics for refugees in transit while guaranteeing a service frequency. The problem is formulated as a multi-period mobile facility location problem with mobile demand (MM-FLP-MD) and a mixed integer linear programming (MILP) model and adaptive large neighborhood search (ALNS) algorithm are presented to solve the problem. Efficiency is defined using a cost objective and the service frequency is set to the highest possible requirement. The model is applied to the Honduras Migration Caravan Crisis in 2018 and the Western Balkan refugee route. The running time of the ALNS algorithm is lower than the MILP model in all instances analyzed while the optimal solution is still found in almost all instances using the ALNS algorithm. The ALNS algorithm thus proves to be an efficient method to overcome the issue of $\mathcal{NP}$-hardness of the MILP problem. Additionally, making the service provision of mobile clinics capacitated increases total costs and the number of clinics that are required.

Contents

1 Introduction

Crossing international borders to find safety from war, violence, conflict or persecution. Having to leave everything known and owned behind. At least 26.4 million refugees are facing this reality (United Nations High Commissioner for Refugees, 2021a). Additional to the number of refugees, at the end of 2020 there were 48 million internally displaced people (IDP), people that did not cross borders when forced to flee (United Nations High Commissioner for Refugees, 2021b).

Several humanitarian organizations help and protect refugees and IDP along their journey. They protect, amongst other things, their right to health (World Health Organization, 2017). Daynes (2016) shows that refugees are at high risk of health problems because of low living standards and limited access to basic sanitation. It is therefore important that health services are regularly provided along the routes that refugees take. To improve the access to primary health services in humanitarian emergencies, mobile clinics can be used. These clinics are fully equipped vehicles providing health services at different locations. Many refugees and people in areas difficult to access are already dependent on mobile clinics for receiving primary health care (World Health Organization, n.d.). However, research on the use and effectiveness of mobile clinics is limited (McGowan et al., 2020). This paper therefore aims to extend research on the efficiency of providing primary health care to refugees in transit using mobile clinics.

Consistent access to basic health care is important in improving public health worldwide. Continuity of care indicates how consistent and interconnected health care events are in satisfying health care needs (World Health Organization, 2018a). The frequency of health services to achieve sufficient continuity of care depends on the type of care. Thus, to determine how to effectively provide health care to refugees using mobile clinics, a service frequency to achieve continuity of care needs to be determined. This paper aims to answer the question: *How to determine the most efficient path of mobile health clinics for refugees in transit while guaranteeing a service frequency?* Therefore, next to determining *service frequency*, a clear objective needs to be determined to define *efficiency*.

To answer the research question, we present a multi-period mobile facility location problem with mobile demand (MM-FLP-MD). Bayraktar et al. (2022) were the first to introduce this relatively new facility location problem (FLP) with both mobile supply and demand and a service frequency. We use and evaluate both the mixed integer linear programming (MILP) model and the adaptive large neighborhood search (ALNS) algorithm presented by Bayraktar et al. To extend the model we present a capacity limitation on the number of refugee groups served by a mobile clinic and analyze its cost-effect. Additionally, we implement a cost objective that consequently minimizes the number of service acts. The analysis uses data from Honduras Migration Caravan Crisis in 2018, provided by Bayraktar et al. (2020). The dataset contains paths followed by refugees over a given time interval. We use this dataset because of the availability and the small size of the problem, which is beneficial for the analysis of results. Additionally, the model is solved for migration data on the Western Balkan route to show that the model can be easily applied to different datasets.

When we define *efficiency* in terms of costs and set the required service frequency to its maximum level, we find optimal solutions both using the MILP model and the ALNS algorithm for both datasets. The running time of the ALNS algorithm is lower than the MILP model in all instances while we still find the optimal solution in almost all instances. Restricting the number of refugee groups that a mobile clinic can provide health care to at a location increases both the average objective value and the number of clinics required. Lastly, adding costs of providing aid to a refugee group to the objective function increases total costs significantly and should therefore be incorporated in the model in the future.

The enormous number of forcibly displaced people shows the social importance of this research. Particularly, the demand for mobile clinics keeps rising, while resources are limited. Finding an optimal path for mobile clinics helps humanitarian organizations to provide more frequent care due to cost and resource reduction. As a result, this paper can contribute to achieving the United Nations Sustainable Development Goals (United Nations, 2020). Moreover, one of the priority actions from a recent gathering about the health of refugees and migrants is to "support new partnerships and innovative ways of working" (Bhatnagar, 2022). Deploying mobile clinics is an example of such an innovative way. Additionally, destination countries of refugees also greatly benefit from continuously and efficiently providing health services to refugees in transit. Namely, providing frequent access to health services to refugees leads to prevention of more serious infections or diseases, with cost savings in the long run as a result (Saleh et al., 2018).

We contribute to the research in the field of Operations Research by analyzing the performance of the MILP model and ALNS algorithm. The extensions continue on the MM-FLP-MD by bringing the model closer to reality. As a result, this paper strengthens the current literature on FLPs.

This paper is structured as follows. Section 2 presents the existing literature related to this paper. Section 3 discusses the problem and assumptions. Next, the mathematical model and solving techniques are presented in Section 4. Section 5 presents the results. Finally, Section 6 discusses the outcomes and concludes.

2 Literature review

The World Health Organization (2018b) states that there is a lack of access to health care for refugees. In addition, refugees experience poor living conditions and greater exposure to infections. To understand the health care needs of refugees, firstly common health conditions of refugees are discussed in Section 2.1. Next, in Section 2.2 these health conditions are quantified and their economic effect is analyzed. Thereafter, mobile clinics and their potential are shortly discussed in Section 2.3. Section 2.4 then explores the existing literature on continuity of care and service frequency. Next, Section 2.5 moves on to the literature related to the mathematical model by outlining the existing research on the FLP. Finally, the literature relevant to the ALNS algorithm is shortly discussed in Section 2.6.

2.1 Common health conditions of refugees

Some knowledge on health problems of refugees is required to identify their health care needs. Firstly, infections and communicable diseases mostly require direct health care and create direct negative health impact. Daynes (2016) states that refugees in transit and in refugee camps are at higher risk of respiratory and gastrointestinal illness and skin diseases. Open fires, bad sanitary conditions and crowded rooms with high humidity are causes of the higher risk of respiratory illnesses. In line with this, the World Health Organization (2016) reports similar health conditions. Most seen skin diseases are rashes, scabies and burns, which all again arise due to poor living conditions.

Next, non-communicable diseases (NCDs), more commonly known as chronic diseases, often have a more long-run negative health impact. However, correct treatment and continuous care of NCDs can drastically increase health of refugees (Daynes, 2016). Namely, NCDs are the greatest cause of death worldwide and disruption of care increases their severity (United Nations High Commissioner for Refugees, n.d.). However, refugees in transit prioritize basic needs such as food and shelter, making continuous treatment of NCDs more difficult.

Several studies also show the high prevalence of anxiety and mental health problems among refugees (Bogic et al., 2015; Fazel et al., 2005). Both in the country of origin and during the flight refugees are exposed to traumatic experiences causing these problems. Particularly, Lindert et al. (2016) report that the traumatic events strengthen the stress and anxiety that refugees already experienced before the flight. For example, refugees fleeing from East Africa to Israel experience trafficking and torture along their journey (Youngmann et al., 2021). Moreover, research on refugees who arrived in Germany between 2013 and 2016 shows that 41.2% of the sample endure some level of psychological distress (Walther et al., 2020).

2.2 Economic effect of health of refugees on destination countries

2.2.1 Cost savings on health care

Next to moral duty and obligation to guarantee the basic human right to health, providing continuous access to health care is also cost-effective. For all previously mentioned health conditions, regular access to health care is necessary. However, van Loenen et al. (2017) show that there exist barriers to health care for refugees, most importantly limited time to attend health services and lack of continuity of care. Failure to maintain a sufficient level of continuity of care increases the likelihood of avoidable hospitalization (Cheng et al., 2010). Moreover, Epstein (2001) showed that access to a free health clinic for low-income populations resulted in significantly lower avoidable hospitalization. Both articles suggest how free and regular access to medical care decreases the likelihood of more extensive medical treatment in the long run.

Trummer et al. (2016) report a potential to reduce costs of health care 49% up to 100% if timely health care treatment is provided to irregular migrants. Irregular migrants are insufficiently documented or unauthorized migrants, which includes a substantial share of refugees (European Commission, 2022). Moreover, the European Union Agency for Fundamental Rights (2015) compares the costs of regular access to health care to irregular access and the resulting cost of emergency treatment for irregular migrants in different European Union Member States. Two different medical conditions were analyzed, both showing significant cost savings if regular access to health care is provided. Namely, regular access to care when having high blood pressure results in cost savings of around 16% over a lifetime. Access to regular parental care resulted in cost savings of around 48% over two years in Germany. Similarly, Daynes (2016) also reports that prevention and early detection of NCDs are more cost-effective than treatment at later stages of the disease.

Looking at the cost of offering mental health care, Ashfaq et al. (2020) report how mental health interventions in their early stages can reduce the severity of mental health issues. However, the study makes use of wireless electronic mental health applications, instead of integrating services in mobile clinics. Nevertheless, Médecins Sans Frontières does underline the importance of adding psychological support to the basic health assessment of mobile clinics in research about mass violence (de Jong, 2014).

2.2.2 Economic impact of refugees

An economic report from the European Commission Directorate-General for Economic and Financial Affairs (2016) shows that 70% of refugees seeking asylum are of working age, defined as 18 to 64 years old. However, the average education level of asylum-seekers is below that of the destination country. Nevertheless, the report stated an expected increase in gross domestic product in the European Union of 0.2% in one year. The potential increase in Germany was even estimated to be 0.4% to 0.8%. However, as highlighted in the report, these numbers depend highly on the development of integration policies. This outlines the potential economic benefit of welcoming refugees with good health and ability to work. Additionally, Taylor et al. (2016) also analyze the impact of refugees on destination countries. The analysis reveals that providing monetary and in-kind aid to refugees results in a significantly higher increase in annual real income in the local economy than if no aid is provided. Specifically, $120 to $126 provision of aid in refugee camps in Rwanda later leads to $205 to $253 in annual real income.

2.3 Mobile clinics

It is however also important to determine the cost-effectiveness of using specifically mobile clinics to offer health services to refugees in transit. Although research on the success of mobile clinics is limited, some papers on specific health conditions highlight their potential. Al-Halaweh et al. (2019) for example show the success of using mobile clinics in diabetes control when local health facilities are limited. This research is especially important due to the high prevalence rate of the NCD diabetes among refugees. Furthermore, Babigumira et al. (2009) examine the cost-effectiveness of using mobile clinics to provide HIV treatment in Uganda. They show that the use of mobile clinics is less cost-effective than fixed health care facilities, but more cost-effective than home-based care. However, Morikawa et al. (2011) prove the effectiveness of providing primary medical care in improving general health by using mobile clinics in remote areas. They show that treatment of infections and communicable diseases is a large share of health care provided by the mobile clinics. Research on the use of mobile clinics along the journey of refugees is however missing, although the required medical services are similar to the previously discussed papers.

2.4 Continuity of care

As highlighted earlier, achieving continuity of care and therefore specifying a required service frequency depends on the type of health care offered. Continuity of care is regularly divided into three types, namely management, relational and informational (Maarsingh et al., 2016). The first refers to the institutional coordination of offering complementary health services. Relational continuity concerns the relationship between patient and health care provider. Lastly, informational continuity assesses the availability of information about one patient to different health care providers. This paper is mostly concerned with management continuity since efficient paths of mobile clinics should contribute to offering regular and coordinated health services. Santa González et al. (2020) optimize continuity of care by quantifying coverage and individual continuity benefits. Different from this, Bayraktar et al. (2022) define the required service frequency as the maximum number of days that are allowed between two health services for each health care type. In their main analysis, they use a required service frequency of three days, although also investigating different requirements. However, to illustrate, for reproductive health care a service frequency of two weeks is sufficient to guarantee continuity of care (Salman et al., 2021). No strict requirements for the minimum service frequency exist for refugees in transit.

2.5 Facility location problem

The problem discussed in this paper is a form of a facility location problem (FLP). The number, position and size of facilities to satisfy demand can be determined in such a problem, and many different constraints can be added to the model (Ghiani et al., 2013). FLPs can be discrete or continuous, referring to their characteristic for space. In continuous models, the facilities can be placed at a point in a continuous space, whereas in discrete models, facilities need to be placed at a point from a finite list of potential locations. This paper models a discrete FLP. Moreover, FLPs can also be divided into two groups based on their time characteristic. Static, or single-period-, FLPs consist of just one period where parameters are fixed. Dynamic, or multi-period-, FLPs consist of various time planning horizons each with possibly different parameter values (Turkoglu & Genevois, 2019). The problem at hand is a dynamic FLP.

The Weber problem is one of the first FLPs. His location triangle aimed to determine the optimal location for production given the location of the market, raw material resources and transportation costs (Weber & Friedrich, 1929). Puerto and Rodríguez-Chía (1999) extend the original Weber problem to locating moving facilities. However, only one facility has to be located in these problems, instead of multiple as in ours. Abdet-Malek (1985) does consider multiple moving facilities. The model presented in this paper determines the initial location and the direction of movement. This differs from our model since facilities do not have to move every period in the same direction and at the same speed.

In dynamic FLPs one could allow facilities to relocate. Such an FLP is called a location-relocation (LR) problem (Boloori Arabani & Farahani, 2012). In our problem, reallocation decisions are made in continuous time, meaning that the relocation is not predetermined. As a result, the reallocation decision now also depends on (variable) reallocation costs. Moreover, the objective of LR problems can take different forms. Trivedi and Singh (2017) show different objectives such as minimization of reallocation distance, minimization of uncovered demand and maximization of facility utilization. A common application of LR problems is the reallocation of emergency medical service (EMS) vehicles. Here a trade-off must be made between the cost of reallocation and the improved demand coverage (Nair & Miller-Hooks, 2009). However, these problems differ from ours in that we have a multi-period model in which not all demand has to be served each period. Rather, a service requirement needs to be fulfilled every predetermined number of periods. Moreover, in EMS vehicle LR problems the vehicle must be located within a specified distance of demand. However, in our problem this distance is zero since mobile clinics can only serve customers when at the exact same location.

Santa González et al. (2020) model a problem close to ours. Namely, they also try to determine the optimal path taken by mobile clinics. Their objective function is specified in terms of continuity of care benefits and they use a multi-period location routing problem (MLRP). However, their problem differs from ours in that demand is not mobile since the mobile clinics are used to visit villages. Moreover, a location cannot be revisited for a predetermined number of days and there is a budget constraint. Mainly the first difference makes their model not suitable for our problem.

Ndiaye and Alfares (2008) also consider the problem of offering health services to moving populations. The objective minimizes total costs, consisting of traveling costs of the customers, fixed costs of opening facilities and variable costs of operating facilities. Moreover, this model also includes utilization requirements, meaning that facilities can only open if there are enough customers assigned to the facility. Fixed and variable costs of operating a facility in this problem are defined similarly to our problem. However, the main contrast between this problem to ours is that facilities are fixed. The problem introduced by Yılmaz and Yücel (2021) differs in its application but considers a similar model. Namely, demand is mobile and costs consisting of a fixed- and operational component need to be minimized. However, the model specified that all demand must be satisfied, whereas in our model demand only needs to be met within a predetermined number of days.

Mobile facility location problems (MFLP) include both moving demand and supply. The objective is to minimize the total facility movement cost and the client travel cost. However, in these problems all customers need to be serviced in each time period (Halper et al., 2015). Raghavan et al. (2019) study the MFLP where the demand that can be satisfied by a facility is capacitated. Both the uncapacitated and capacitated MFLP are proven $\mathcal{NP}$-hard and these papers therefore introduce algorithms to solve the model. Besides that, in our problem, demand moves through the network but does not move to a mobile clinic specifically, which differs from the MFLP.

Another type of location problem is flow capturing models (FCMs). In these types of problems, facilities are located on customer paths to satisfy their demand (Turkoglu & Genevois, 2019). Demand is thus mobile in these problems, but supply is fixed. Moreover, the time horizon is only one period. Thus, this problem needs to become more general to fit our problem. A flow intercepting facility location problem (FIFLP) is similar to the FCM in that demand is mobile, following a predetermined path. However, now also supply can be made mobile. Sterle et al. (2016) present a FIFLP with multiple periods (MP-FIFLP). Moreover, Boccia et al. (2009) present different objectives of the FIFLP such as maximization of the intercepted flow and maximization of the achievable gain together with heuristics to solve the models. These problems however differ from ours in that in our problem mobile demand and supply only have to be at the same location each predetermined number of days. Thus, the service frequency is again differently defined in this model.

Evacuation problems also have similarities to our problem. Evacuation problems consider the flow of traffic having to escape a building or region in case of an emergency (Bretschneider & Kimms, 2011). Similar to our problem, demand is mobile. However, in evacuation problems the demand can be set to follow an optimal path, whereas refugees choose their own route.

As becomes clear from the review so far, the problems considered until now do not include the minimal service frequency requirement. However, vertex cover problems do have such a requirement, called the coverage requirement. This can be seen by looking at the k-path vertex cover (k-PVC) problem. Note that when $k = 2$, the problem corresponds to the vertex cover problem, which is $\mathcal{NP}$-hard. A subset of vertices S from all vertices in the graph $V(G)$ is called a k-path vertex cover if every path of length k contains at least one vertex of S (Brešar et al., 2011). The objective of vertex cover problems is to find the vertex cover of graph G that contains the least possible number of vertices. A different type of vertex cover problem is the N-distance minimal vertex cover problem (Yadav et al., 2016). Here, every vertex must be at most N edges away from a vertex in S. However, vertex cover problems do not include moving supply and demand in the graph over multiple periods. As a result, these problems cannot specify that in some periods vertices do need to be covered, while in others not.

Finally, Bayraktar et al. (2022) introduce a multi-period FLP with mobile demand and periodic service requirement matching our problem. They are the first to introduce this form of an FLP and prove the $\mathcal{NP}$-hardness. Note that the objective in Bayraktar et al. (2022) is based on a fixed and variable cost component related to the cost of opening mobile clinics and moving mobile clinics respectively. This paper will extend the cost specification by adding an operational cost component. Moreover, there is no capacity constraint on the number of refugee groups serviced by a mobile clinics, which will also be added to the model.

Table 1 gives an overview of the problems and their characteristics that are discussed in this section.

Table 1. Overview of problems related to the FLP

problem	**mobile facility**	**mobile demand**	**horizon**	**service frequency**	**objective**
Weber	yes	no	dynamic	each period	min. distance
LR	yes	no	dynamic	each period	min. distance/ uncovered demand
MLRP	yes	no	dynamic	optimal	max. continuity of care benefits
MFLP	yes	yes	dynamic	each period	min. distance
MP-FIFLP	yes	yes	dynamic	threshold value	min. cost
Evacuation	no	yes	dynamic	none	min. time
k-PVC	no	no	static	none	min. cost
MM-FLP-MD	yes	yes	dynamic	every τ periods	min. cost

2.6 ALNS algorithm

Since the MM-FLP-MD is proven to be $\mathcal{NP}$-hard, Bayraktar et al. (2022) also provide the implementation of an ALNS algorithm to solve larger instances of the problem. The algorithm is based on the large neighborhood search (LNS) algorithm introduced by Shaw (1998). To find an optimal solution, a large neighborhood of the current solution is explored by destroying part of the current solution and performing repair operations to again obtain a new feasible solution. The ALNS algorithm extends this idea by making use of multiple destroy- and repair operations. Ropke and Pisinger

(2006) first introduce this extension and use a roulette wheel to randomly select the destroy- and repair operation that is going to be used. To determine the share of the operation on the roulette wheel, weights are assigned to the operations. These weights are based on the performance of the operator, where a good performing operator gets a larger weight. They also discuss several destroy operations that will be used in the ALNS algorithm in this paper. For the repair operations, regret insertion is introduced by Potvin and Rousseau (1993) for the Vehicle Routing and Scheduling Problem with Time Windows. It uses a generalized regret measure to find the best insertion point over all unrouted customers. We will similarly define such a regret measure to use this repair operation in the ALNS algorithm. To end the ALNS algorithm, acceptance criteria of the simulated annealing metaheuristic can be used (Kirkpatrick et al., 1983). This method is often used to find a global optimum when many local optima exist. Namely, a solution worse than the current solution can still be accepted with some probability to enable escaping a local optimum.

3 Problem description

The MM-FLP-MD will be used to find the optimal path for mobile clinics to serve refugees. To do so, we define a directed network $G = (V, A)$. Moreover, we introduce two subnetworks, one for mobile clinics, and the other one for refugee groups. The subnetwork for mobile clinics is denoted by $G_\nu = (V_\nu, A_\nu)$. Here, $V_\nu \subseteq V$ are the nodes in the network on which a mobile clinic can be placed. Furthermore, $A_\nu \subseteq A$ are the arcs in the network on which mobile clinics can move from one node to another. The subnetwork for refugee groups is denoted by $G_\rho = (V, A_\rho)$. Similarly, V are the nodes in the network which serve as a stopover point for refugees and $A_\rho \subseteq A$ are the arcs in the network on which refugee groups move from one node to another. Note that subsets might be incomplete due to the maximum distance mobile clinics and refugee groups can travel.

Refugee groups travel on the network from a source node to a destination node. Refugees that follow the same path at the same time are considered one refugee group. There are a limited number of paths p that refugee groups can take. We denote the set containing all paths by P. Further, we assume that each period a refugee group travels to the next node on their path. This paper only treats deterministic problems. Thus, we assume that all movements of refugee groups are known exactly.

Next, the planning horizon, denoted by T, is the number of periods for which the problem is solved. This is determined by the minimum time at which all refugee groups have entered and left the network.

We denote the set containing all mobile clinics by M. Mobile clinics have fixed and variable costs. The fixed cost of mobile clinic $m \in M$ is denoted by f_m, which is the cost to set up a mobile clinic for services. Note that the indices, and thus the mobile clinics, are sorted in non-decreasing order, i.e. $f_m \leq f_{m+1}$. In the extension of the model, the variable costs can be divided into two components, c_{ij} and o_{ts}. The former denotes the transportation cost of moving a mobile clinic from node i to node j. The latter denotes the operation cost of serving a refugee group that has been in transit for $t - s$ periods. We assume that the starting node of the mobile clinic can be chosen freely.

For a mobile clinic to provide service to a refugee group, the requirement is that they must be at the same node and in the same time period. Continuity of care requires all refugee groups to be served at least once every τ periods.

Lastly, we introduce some terminology. A node-time pair, denoted as $\sigma = (n, t)$, is the state of being at node n in time period t. Additionally, the node of the node-time pair σ can be referred to as $n(\sigma)$. Likewise, the time of node-time pair σ is referred to as $t(\sigma)$. Furthermore, a service act is a mobile clinic providing service to a refugee group at node $n \in V$ in period $t \in T$. Thus, a node-time pair (n, t) is a service act if both a mobile clinic and a refugee group are at node n in period t. Then, a service act sequence of a mobile clinic, denoted by ϕ, is a list of service acts ordered by increasing time periods. The i^{th} service act in ϕ is accessed using $\phi(i)$.

4 Methodology

The following mathematical model, introduced by Bayraktar et al. (2022), is used to solve the MM-FLP-MD. We start by defining the sets, parameters and decision variables in Table 2.

Table 2. Sets, parameters and decision variables of the MM-FLP-MD

Sets	
P	set of refugee paths
V	set of nodes in network G
V_ν	set of nodes in subnetwork of mobile clinics
A	set of arcs in network G
A_ν	set of arcs in subnetwork of mobile clinics
A_ρ	set of arcs in subnetwork of refugee groups
M	set of mobile clinics
T	set of time periods

Parameters	
d_{pt}	whether refugee enters path p in time period t ($d_{pt} = 1$), or not ($d_{pt} = 0$)
a_i	whether mobile clinics can be located on node i ($a_i = 1$), or not ($a_i = 0$)
l_p	number of nodes on path p
n_{pk}	k^{th} node on path p
f_m	fixed cost component of using mobile clinic m
c_{ij}	transportation cost of moving mobile clinic from node i to node j
τ	minimum service frequency in days
Decision variables	
Y_{imt}	whether mobile clinic m is at node i in time period t ($Y_{imt} = 1$), or not ($Y_{imt} = 0$)
X_{ijmt}	whether mobile clinic m travels from node i to j at the end of time period t ($X_{ijmt} = 1$), or not ($X_{ijmt} = 0$)
Z_m	whether mobile clinic m is utilized ($Z_m = 1$), or not ($Z_m = 0$)

4.1 MILP model

The mathematical model is defined as follows.

$$\min \quad \sum_{m \in M} f_m Z_m + \sum_{(i,j) \in A_\nu} \sum_{m \in M} \sum_{t \in T} c_{ij} X_{ijmt} \tag{1}$$

$$\text{s.t.} \quad \sum_{i \in V_\nu} Y_{imt} = Z_m \qquad \forall m \in M, \forall t \in T \tag{2}$$

$$\sum_{m \in M} \sum_{t'=0}^{\tau-1} Y_{(n_{p,k+t'+1}),m,t+k+t'} \geq d_{pt} \qquad \forall p \in P, 0 \leq k \leq l_p - \tau, t = 1, \ldots, |T| - l_p + 1 \tag{3}$$

$$Y_{imt} \leq a_i Z_m \qquad \forall i \in V, \forall m \in M, \forall t \in T \tag{4}$$

$$Y_{imt} + Y_{j,m,t+1} - X_{ijmt} \leq 1 \qquad \forall (i,j) \in A_\nu, \forall m \in M, t = 1, \ldots, |T| - 1 \tag{5}$$

$$Y_{imt} \leq X_{ijmt} \qquad \forall i, j \in V_\nu, \forall m \in M, t = 1, \ldots, |T| - 1 \tag{6}$$

$$Y_{j,m,t+1} \geq X_{ijmt} \qquad \forall i, j \in V_\nu, \forall m \in M, t = 1, \ldots, |T| - 1 \tag{7}$$

$$\sum_{j \in V_\nu : (i,j) \in A_\nu} X_{i,j,m,t+1} = \sum_{j \in V_\nu : (j,i) \in A_\nu} X_{jimt} \qquad \forall i \in V_\nu, \forall m \in M, t = 1, \ldots, |T| - 1 \tag{8}$$

$$Y_{imt} \in \{0, 1\} \qquad \forall i \in V, \forall m \in M, \forall t \in T \tag{9}$$

$$X_{ijmt} \in \{0, 1\} \qquad \forall (i,j) \in A_\nu, \forall m \in M, t = 1, \ldots, |T| - 1 \tag{10}$$

$$Z_m \in \{0, 1\} \qquad \forall m \in M \tag{11}$$

The objective function (1) minimizes the fixed cost of setting up mobile clinics and the transportation cost of moving mobile clinics through the network. Thus, efficiency is determined in terms of cost. Constraints (2) ensure that all mobile clinics that provide service are utilized. Constraints (3) define the requirement for service frequency. It ensures that all refugee groups that enter the network are serviced at least every τ days. Next, constraints (4) restrict mobile clinics only to be placed on nodes that are in that subnetwork. Constraints (5) to (7) define the relationship between decision variables. It sets $X_{ijmt} = 1$ if $Y_{imt} = 1$ and $Y_{j,m,t+1} = 1$. Constraints (8) ensure that the move of a mobile clinic is defined for each period. Constraints (9) to (11) restrict the domain of the decision variables to be binary. Note that Bayraktar et al. (2022) prove that without losing feasibility and optimality the integrality constraints on the X and Z variables can be relaxed.

4.1.1 Capacity limitation and operating cost

Next, we will introduce a capacity limitation for mobile clinics on the number of refugee groups served at one node. To do so, decision variable W_{imtps} is introduced. Namely, W_{imtps} denotes whether the refugee group that starts path p at time period s is served by mobile clinic m at node i in time period t ($W_{imtps} = 1$), or not ($W_{imtps} = 0$). Firstly, we add the constraints

$$Y_{imt} \geq W_{imtps}, \quad \forall i \in V, \forall m \in M, \forall s \leq t \in T, \forall p \in P, \tag{12}$$

which ensure that a refugee group can only be served if both a mobile clinic and the refugee group are at the same node at the same time. Moreover, constraints (3) are replaced by

$$\sum_{m \in M} \sum_{t'=0}^{\tau-1} W_{(n_{p,k+t'+1}),m,s+k+t',p,s} \geq d_{ps}, \quad \forall p \in P, 0 \leq k \leq l_p - \tau, s = 1, \ldots |T| - l_p + 1, \tag{13}$$

to ensure that all refugee groups are served at least every τ days. Moreover, we add the domain restriction $W_{imtps} \in \{0, 1\}, \forall i \in V, \forall m \in M, \forall s \leq t \in T, \forall p \in P$. Then we can introduce the constraint restricting a mobile clinic to serve at most C refugee groups each time period

$$\sum_{p \in P} \sum_{s=t}^{|T|} W_{imtps} \leq C, \quad \forall i \in V, \forall m \in M, \forall t \in T. \tag{14}$$

Note that constraints (12) and (14) can be combined into one constraint,

$$\sum_{p \in P} \sum_{s=t}^{|T|} W_{imtps} \leq CY_{imt}, \quad \forall i \in V, \forall m \in M, \forall t \in T. \tag{15}$$

By the introduction of W_{imtps} we can now also include a cost of serving refugee groups at a mobile clinic. This cost is dependent on how many periods the refugee group is already in transit. The component $\sum_{i\in V}\sum_{m\in M}\sum_{t\in T}\sum_{P\in P}\sum_{s=t}^{|T|} o_{ts}W_{imtps}$ is added to the objective function, where o_{ts} is the operating cost of serving a refugee group that is already in transit for $t-s$ periods.

4.2 ALNS algorithm

As shown by Bayraktar et al. (2022), the MILP problem as defined before is $\mathcal{NP}$-hard. Therefore, they introduce the ALNS algorithm to solve the problem with a shorter running time.

The pseudo-code of the complete algorithm can be found in Algorithm 1. We will firstly describe the outline of the algorithm before going into detail about the operations. The algorithm begins with an initial solution s_0. Both the current solution s and the best found solution s_{best} are set equal to this initial solution. Next, weights of repair- and destroy operations are initialized to decide what repair- and destroy operations are going to be used. In each iteration, a repair operation, h_{repair}, and destroy operation, $h_{destroy}$, on the current solution obtains a new solution s'. The new solution s' is used in the next iteration if s' has a better total cost value than s, or if the acceptance criteria of simulated annealing accept s'. Moreover, s_{best} is set to s' if the total cost value of s' is lower. The algorithm performs better if a local search (LS) procedure is applied every ζ iterations. Furthermore, the weights of the repair- and destroy operations are adjusted every η operations. Finally, stopping criteria determine when the algorithm stops and returns s_{best} after performing another LS.

4.2.1 Solution representation

To use the algorithm, we need to be able to keep track of the current solution and its feasibility. Therefore, some additional terminology is introduced.

The time-indexed path $\pi(p,t)$ is a sequence of node-time pairs of a refugee group that starts path p in time period t. Then, the i^{th} node-time pair of time-indexed path π is denoted by $\pi(i)$. Π is the set containing all time-index paths of an instance.

Next, the feasible service act sequence (FSAS) of a time-indexed path π is the subset that only contains the node-time pairs at which the refugee group receives service such that the service frequency requirement is satisfied for that group. As proposed by Bayraktar et al. (2022), a service act sequence (SAS), denoted by ϕ, is an FSAS of time-indexed path π if the following three conditions are met:

1. Each node-time pair in ϕ must be in time-indexed path π, i.e. $\phi \subseteq \pi$.

2. The number of time periods between two consecutive service acts in ϕ must be at most $\tau - 1$, i.e. $t(\phi(i+1)) - t(\phi(i)) \leq \tau, \forall i = 1, \ldots, |\phi| - 1$.

3. The first and last service acts in ϕ must be among the first and last τ node-time pairs in π, respectively.

The visit schedule, v^m, is the sequence of time-ordered node-time pairs that mobile clinic m traverses. If a mobile clinic is at node-time pair (n, t) and this node-time pair exists in any time-indexed path π, then a service act σ is performed by the mobile clinic at (n, t). Note that the nodes of consecutive node-time pairs can be the same if the mobile clinic does not change location.

The solution is presented as the set of visit schedules of all utilized mobile clinics, $s = \{v^1, \ldots, v^m\}$, where m is the number of mobile clinics utilized. The solution shows at what node-time pairs service acts σ are performed. However, the solution can also be represented as the time-indexed path of refugee groups, showing at what node-time pairs they receive service. Note that if a time-indexed path does not have an FSAS, the path is called an uncovered time-indexed path and the solution is infeasible. To have a feasible solution, at least one FSAS needs to exist for every time-indexed path.

4.2.2 Minimal FSAS

To find the optimal solution, the minimal, or non-dominated, FSAS needs to be found among the set of FSAS of a time-indexed path. An FSAS of time-index path π is dominated if a service act $\phi(i)$ can be removed from the SAS ϕ and the resulting service act sequence is still an FSAS of π (Bayraktar et al., 2022). The set of all minimal FSAS of time-indexed path π is denoted by Φ'_π. We use Algorithm 2 introduced by Bayraktar et al. (2022) to derive all Φ'_π. To start, Φ_π and Φ'_π are initialized as empty sets, where Φ_π becomes a set of SASs. Next, an SAS for all first τ node-time pairs of π is created by adding that node-time pair into the SAS ϕ_i if a mobile clinic can be located at the corresponding node. The SAS ϕ_i is then inserted into Φ_π. Afterward, the first SAS, say ϕ, in Φ_π is removed and τ new SASs based on ϕ are created. A new SAS $\overline{\phi}$ is created by adding a service act for one of the subsequent τ node-time pairs of π at the end of ϕ. If this new SAS is dominated, the sequence is neglected. However, if the last service act of $\overline{\phi}$ is one of the last τ node-time pairs of π, then the sequence is a minimal FSAS of π and is added to Φ'_π. Else, the new sequence is again added to Φ_π. This process is repeated until Φ_π is empty. The algorithm returns the set of minimal FSAS of π, Φ'_π.

4.2.3 Destroy operators

In line 17 of Algorithm 1, a destroy operation is used. A destroy operation destroys a current solution s by removing κ service acts from s. Here, κ is a random number from the set $\{\underline{\kappa}, \underline{\kappa}+1, \ldots, \overline{\kappa}\}$, with $\underline{\kappa} = [b_1|s|]$ and $\overline{\kappa} = [b_2|s|]$. The destroy degree parameters b_1 and b_2 have a value between zero and one. The number of service acts in the solution s is $|s|$. The algorithm uses three different destroy operations.

Random Service Act Removal (RSAR)

This destroy operator iteratively removes κ service acts by randomly selecting a service act that is provided by a random mobile clinic. The service act is removed from the visit schedule of the randomly selected mobile clinic.

Random Mobile Clinic Removal (RMCR)

This destroy operator always removes the entire visit schedule of a mobile clinic. The mobile clinic is selected randomly, and all its service acts are removed from the solution. The operator continues until at least κ service acts are removed.

Shaw Removal (SR)

This destoy operation follows the ideas of Shaw (1997) and Shaw (1998) that removing related components is more favorable. To determine the relation between two service acts (σ_1 and σ_2), a relatedness measure R is defined as follows.

$$R(\sigma_1, \sigma_2) = w_1 \frac{c_{n(\sigma_1),n(\sigma_2)}}{\max_{(i,j)\in A}\{c_{ij}\}} + w_2 \frac{|t(\sigma_1) - t(\sigma_2)|}{|T|} + w_3(1 - \frac{2h(\sigma_1, \sigma_2)}{H(\sigma_1, \sigma_2)}) \tag{16}$$

Here, w_1, w_2 and w_3 are weight parameters. Moreover, $h(\sigma_1, \sigma_2)$ is the number of refugee groups that σ_1 and σ_2 both serve and $H(\sigma_1, \sigma_2)$ is the sum of the number of refugee groups that are served by σ_1 and σ_2. The first component of equation (16) is the normalized distance between the nodes of σ_1 and σ_2. The second component is the normalized difference between their time periods. Finally, the last component is the number of different refugee groups that σ_1 and σ_2 serve as a percentage of the total number of groups served by them. As R approaches zero, the service acts become more related. To start the destroy operation, a random service act σ is removed from the solution and added to the set of removed service acts D. To select the next service act that is going to be removed, we determine what service act in s is most related to a randomly selected service act from D. This service act is removed from s and inserted into set D. This process is repeated until κ service acts are removed.

4.2.4 Repair operators

In line 17 of Algorithm 1, a repair operation is used. To do so, the operator determines what time-indexed paths currently have no FSAS and inserts service acts to get one of its FSASs. Inserting a service act is always done such that the total cost increase is minimal. The repair operator continues until all uncovered time-indexed paths are covered. To start a repair operator, a new mobile clinic is added to the solution to prevent infeasibility. If the newly inserted mobile clinic does not perform any service acts, the clinic is again removed from the solution at the end of the operation. The algorithm uses four different repair operations.

Random FSAS Insertion (RFI)

This repair operator selects a random uncovered time-indexed path π. Next, it selects a random minimal FSAS of π called $\tilde{\phi}_\pi$ from the set of minimal FSASs Φ'_π. The service acts that are in $\tilde{\phi}_\pi$ but not in the current solution are inserted into the solution by adding them to the visit schedule of a mobile clinic.

Least Cost FSAS Insertion (LCFI)

The repair operator randomly selects uncovered time-indexed path π. Next, it selects a minimal FSAS of π called $\tilde{\phi}_\pi$ from the set of minimal FSASs Φ'_π that results in the smallest total cost increase when the missing service acts are added to the solution. The service acts that are in $\tilde{\phi}_\pi$ but not in the current solution are inserted into the solution by adding them to the visit schedule of a mobile clinic.

Worst Insertion (WI)

The repair operator selects random uncovered time-indexed path π. Next, it selects an FSAS of π called $\tilde{\phi}_\pi$ that results in the largest total cost increase when the missing service acts are added to the solution. Note that the worst FSAS of π is π itself. The service acts that are in π but not in the current solution are inserted into the solution by adding them to the visit schedule of a mobile clinic.

n-Regret Insertion (RI-n)

First, all minimal FSASs of uncovered time-indexed path π are sorted in non-decreasing order of cost increase when the missing service acts would be inserted into the solution. The k^{th} item in this list is the k^{th} best minimal FSAS of π and can be denoted as $\phi^{\pi,k}$. Moreover, $\Delta z_{\phi^{\pi,k}}$ is the increase in objective function if the service acts of $\phi^{\pi,k}$ that are missing in the current solution are inserted into the solution. Here, instead of selecting a random uncovered time-indexed path, the operator selects an uncovered time-index path π^* using the following equation.

$$\pi^* = \underset{\pi \in \Pi}{\text{argmax}}\{ \sum_{k=2}^{\min\{n, |\Phi'_\pi|\}} (\Delta z_{\phi^{\pi,k}} - \Delta z_{\phi^{\pi,1}})\} \tag{17}$$

The service acts that are in π^* but not in the current solution are inserted into the solution by adding them to the visit schedule of a mobile clinic.

4.2.5 Selecting destroy and repair operations

To select a destroy- and repair operator a roulette-wheel selection procedure is used for both selection procedures separately. Each operation has an angle proportional to its weight on the wheel. Here, ω_i denotes the weight of destroy- or repair operator i. The weights are adjusted every η operations by recalculating the weight as

$$\omega_i^{new} = \begin{cases} (1-\rho)\omega_i + \rho\frac{\beta_i}{\upsilon_i}, & \text{if } \upsilon_i \neq 0, \\ (1-\rho)\omega_i, & \text{if } \upsilon_i = 0, \end{cases} \tag{18}$$

where ρ is the reaction factor that controls the rate at which the weight adjustment takes place. Moreover, υ_i denotes the number of times operator i is used in the last η operations. Lastly, β_i denotes the score of operator i. The score is determined as follows. At the end of each iteration in Algorithm 1, if the recovered solution s' is accepted using the acceptance criteria, and

- if the recovered solution s' improves the best solution s_{best}, then the scores of the destroy and repair operator used in that iteration are increased by ϵ_1;
- if the recovered solution s' only improves the current solution s, then the scores of the destroy and repair operator used in that iteration are increased by ϵ_2;
- if the recovered solution s' does not improve the current solution s nor best solution s_{best}, then the scores of the destroy and repair operator used in that iteration are increased by ϵ_3.

Note that when the weights of all operators are updated, the weights are normalized in their own sets and all υ_i and β_i are reset to 0.

4.2.6 Initial solution

As can be seen in Algorithm 1, the algorithm uses the initial solution s_0 as input. The Constructive Heuristic (CH) as described by Bayraktar et al. (2022) is used to obtain this initial solution. To start, time-indexed path π is randomly selected from Π. If time-indexed path π is already covered, we move on to the next iteration. If not, we determine the minimal FSAS of π called $\tilde{\phi}_\pi$ from the set of minimal FSASs Φ'_π that results in the smallest total cost increase when the missing service acts are added to the partial solution s_0. The service acts that are in $\tilde{\phi}_\pi$ but not in the current s_0 are inserted in s_0 by adding them to the visit schedule of a mobile clinic. This procedure is repeated until all time-indexed paths in Π are covered. Lastly, we traverse the visit schedules of all mobile clinics to identify the service acts. Note that a node-time pair (n, t) of a visit schedule v^m is a service act if the node-time pair also exists in a time-indexed path π.

4.2.7 Local Search

As can be seen in Algorithm 1, an LS is performed every ζ iterations. Two operations can be distinguished in an LS. The first operation is a service act removal. We traverse all service acts of all visit schedules to determine whether removing a service act from a visit schedule results in an uncovered time-indexed path. If not, then this service act is removed from the visit schedule. The second operation is a service act transfer or swap. We traverse over all visit schedules to determine whether a better solution can be found by transferring a service act of a visit schedule to another visit schedule or swapping service acts of two visit schedules. This is done as follows. If we have a service act at node-time pair σ_i of visit schedule v^m, we check all other visit schedules for a potential transfer or swap. Let $v^{m'}$ be one such other visit schedule. If $v^{m'}$ does not perform a service act in the corresponding time period $t(\sigma_i)$, the service act at node-time pair σ_i is removed from v^m and inserted into $v^{m'}$. If $v^{m'}$ does perform a service act in the corresponding time period $t(\sigma_i)$, the service act at node-time pair σ_i and σ'_i are removed from v^m and $v^{m'}$ and inserted into $v^{m'}$ and v^m respectively. Note that here σ'_i is the node-time pair corresponding to the service act in $v^{m'}$ at time $t(\sigma_i)$, and $t(\sigma_i) = t(\sigma'_i)$. If we define $\Delta z^{\sigma,m,m'}$ as the change in total cost if service act σ of v^m is transferred to $v^{m'}$ or swapped with a service act in $v^{m'}$, then a negative value of $\Delta z^{\sigma,m,m'}$ signals a total cost reduction. Now, a transfer or swap of σ is performed for visit schedule v^{m^*} if $\Delta z^{\sigma,m,m^*} < 0$, where $m^* = \text{argmin}_{m'} \Delta z_{\sigma,m,m'}$. This procedure is repeated until all service acts of all visit schedules are traversed.

4.2.8 Acceptance and stopping criteria

As can be seen in Algorithm 1, at the end of each iteration, in line 21, the acceptance criteria determine whether the newly found solution s' becomes the solution in the next iteration. The acceptance criteria is that of the simulated annealing metaheuristic (Kirkpatrick et al., 1983). Namely, s' is accepted as a new solution if the solution is better than s, i.e. the total costs are lower. Moreover, if s' is not an improvement on s, it is accepted as a new solution with probability $e^{\frac{z(s)-z(s')}{temp_{iter}}}$. Here, $z(s)$ is the objective value of solution s, i.e. the total cost, and $temp_{iter}$ is the temperature of the iteration. To determine $temp_{iter}$, the temperature is initialized as $temp_0 = \frac{z(s_0)}{\ln(2)}$, and updated in each iteration with $temp_{iter} = \alpha \ temp_{iter-1}$, where α is the parameter representing the cooling rate. Algorithm 1 finishes when a predefined number of iterations χ_1 is reached or when a predefined number of non-improving solutions χ_2 is reached.

4.2.9 Capacity limitation and operating cost

To include the capacity limitation on mobile clinics as described in Section 4.1.1, a few changes must be made to the ALNS algorithm. Namely, if a node-time pair (n, t) exists in both a time-indexed path π and visit schedule v^m, then mobile clinic m does not automatically serve the refugee group corresponding to π. Therefore, in the visit schedule, next to denoting the node-time pairs on the path of a mobile clinic, we should also keep track of how many refugee groups are served at each node-time pair. We set $\psi_{m\sigma}$ to be the number of refugee groups served by mobile clinic m at node-time pair σ. If we restrict this number to be at most C we can ensure that a mobile clinic can only serve a limited number of refugee groups each time period. Consequently, the capacity constraint must be checked in the repair operation, construction of initial solution and local search transfer or swap when adding service acts to refugee groups. Similar to the MILP model, we can now also add an operating cost of mobile clinics providing service to a refugee group at a specific node-time pair by checking $\psi_{m\sigma}$.

5 Results

5.1 Honduras Migration Caravan Crisis in 2018

5.1.1 Data generation

This section of the results uses data from the Honduras Migration Caravan Crisis in 2018, which is provided by Bayraktar et al. (2020). This dataset contains 75 instances, divided into 25 small-sized instances with a total of 10 nodes, 25 medium-sized instances with 20 nodes and 25 large-sized instances with 30 nodes. The large-sized instances contain the full network, whereas the small- and medium-sized instances contain a smaller section of the network. Each instance contains the exact paths that refugee groups started and in what time period. Moreover, it contains the cost for mobile clinics of traveling over the arcs. Note that the data is based on the actual refugee movement that started in October 2018, where refugees started their journey from Central America to the United States.

A detailed description of the construction of the dataset can be found in Bayraktar et al. (2022). In total there are 21 primary nodes and 9 secondary nodes, thus $|V| = 30$ and $|V_\nu| = 21$. This signals that refugee groups might not cross nodes in V_ν for multiple time periods. As a result, the problem becomes infeasible if we set $\tau = 1$ or $\tau = 2$. Therefore, in this case we set $\tau = 3$.

Not all instances that are available are used in this paper. We examine 10 small-sized, 10 medium-sized and 5 large-sized instances. The chosen instances are presented in Table C1. As shown in the table, the name of the instances consists of four parts. Specifically, P shows the number of paths in the instance, E the number of refugee groups, N the number of nodes and the last number differentiates the instances with the same properties.

The costs in this network initially consist of two components. The cost of a mobile clinic to travel from node i to j, c_{ij} , is defined as the shortest distance from node i to j. Therefore, the fixed costs are also determined in terms of distance. To do so, the costs are first determined in terms of euros, whereafter a unit cost per kilometer is determined. The costs presented in Bayraktar et al. (2022) are used. The unit travel cost per kilometer is €1.31/km for the Honduras Migration Caravan Crisis such that the fixed costs of using a mobile clinic in terms of distance are set to 600km.

5.1.2 Computational performance

In this section, we compare the results of using the MILP model and ALNS algorithm to solve the Honduras Migration Caravan Crisis network. The mathematical model is solved using CPLEX for

Java. Moreover, a limit on the optimality gap is set to 0.01% and the run-time to 4 hours. For the ALNS algorithm, the same parameter values are used as in Bayraktar et al. (2022). A short description of the programming code is given in Appendix B.

Table 3 summarizes the results of the selected instances. The optimal objective is retrieved from Bayraktar et al. (2022). The best objective value for the ALNS algorithm is the best value found from running the algorithm eight times and the running time corresponds to this best run.

Table 3. MILP model and ALNS algorithm results Honduras Migration Caravan Crisis

		best objective			**run-time**	
Name	**optimal objective**	**MILP**	**ALNS**	**objective difference**	**MILP**	**ALNS**
P01E01N10_1	1100	1100	1100	0.00 %	1	1
P01E02N10_1	1100	1100	1100	0.00 %	1	1
P02E04N10_1	1356	1356	1356	0.00 %	1	1
P02E04N10_2	1669	1669	1669	0.00 %	1	1
P03E06N10_1	1720	1720	1720	0.00 %	2	2
P03E06N10_2	1356	1356	1356	0.00 %	1	1
P04E08N10_3	1989	1989	1989	0.00 %	20	2
P04E08N10_4	1990	1990	1990	0.00 %	7	2
P06E10N10_1	2082	2082	2082	0.00 %	7	3
P06E10N10_2	2063	2063	2063	0.00 %	4	3
P01E01N20_1	1488	1488	1488	0.00 %	10	5
P01E02N20_1	1492	1492	1492	0.00 %	8	4
P02E04N20_1	1839	1839	1839	0.00 %	33	12
P02E04N20_2	2594	2594	2594	0.00 %	2684	12
P03E06N20_1	2910	2910	2910	0.00 %	14400	85
P03E06N20_2	2372	2372	2372	0.00 %	3245	252
P04E08N20_3	2940	2940	2941	-0.03%	14036	117
P04E08N20_4	3093	3093	3093	0.00%	14403	115
P06E10N20_1	3215	3285	3222	1.96%	14405	167
P06E10N20_2	3244	3244	3244	0.00%	14407	140
P01E01N30_1	2129	2129	2129	0.00 %	127	18
P01E02N30_1	2133	2133	2133	0.00 %	435	86
P02E04N30_1	2883	2883	2883	0.00 %	10278	150
P02E04N30_2	4098	4214	4098	2.83%	14401	50
P06E13N30_1	4899	6647	4899	35.68%	14404	2802
			minimum	-0.03%	1	1
			maximum	35.68%	14407	2802
			average	1.62%	4117	161

Note. Objectives are expressed in distance (km); *objective difference* is the difference between MILP model and ALNS algorithm; run-times are in seconds and rounded up to the nearest second.

The ALNS algorithm is quickly able to find good solutions. Namely, from Table 3 we observe that the MILP model was able to find the optimal objective value for 22 out of 25 instances. The ALNS algorithm was able to find the optimal objective value for 23 out of 25 instances. For only one instance the MILP model was able to find a better solution than the ALNS algorithm, which differs by 1. Moreover, the running times of the ALNS algorithm are never exceeding those of the MILP model. The average running time is even 25.6 times lower for the ALNS algorithm than for the MILP model.

The reported objective values found using the ALNS algorithm are similar to those found in Bayraktar et al. (2022). An important difference is however that they find the optimal solution for all medium-sized instances at least once in eight runs and we do not. Moreover, they do not always find the optimal solution for the large-sized instances, whereas we do. This difference can be explained by the randomness in the construction of the initial solution and the destroy- and repair operation.

Furthermore, our running times deviate from those reported in Bayraktar et al. (2022). For the MILP model the reported average running time over all instances lie close together. The running times for the ALNS algorithm in our results are however on average four times lower than the running times presented in Bayraktar et al. (2022). This can be caused by differences in programming the algorithm and as a result the efficiency of the program.

5.1.3 Analysis instance P06E13N30_1

To show how the solution of the MILP model and ALNS algorithm can be presented and analyzed, we further explore the solution of the largest instance P06E13N30_1. The problem consists of 6 different paths and 13 refugee groups in total starting on these paths. The time horizon is 35 periods. Table C2 and Table C3 in Appendix C present the best found solution of the MILP model and ALNS algorithm respectively for the service acts of mobile clinics. The solution of the MILP model uses three mobile clinics together performing 58 service acts. Therefore, the fixed costs are 1800 and the traveling cost 4847, resulting in a total cost of 6647. Table C4 shows when each refugee group gets serviced. The ALNS algorithm found the optimal solution, using three mobile clinics that together perform 51 service acts. The fixed costs are again 1800 and the traveling cost 3099, giving a total cost of 4899. Table C5 shows when each refugee group gets serviced.

The ALNS algorithm finds a solution where refugee groups receive service more efficiently. Namely, if we define the utilization level as the percentage of periods that mobile clinics perform a service act, then the levels are 55% and 49% for the MILP model and ALNS algorithm respectively.

Moreover, the service frequency is on average 0.37 and 0.30 received service acts by a refugee group per time period for the MILP model and ALNS algorithm respectively.

Lastly, using mobile clinics instead of immobile clinics leads to cost-savings. We compare the best found solution of the ALNS algorithm to the optimal solution for immobile clinics. For the latter, 10 clinics are needed and the total cost is hence 6000. Thus, the objective value decreases by 18.4% if the ALNS algorithm with mobile clinics is used compared to solving the model with immobile clinics.

5.1.4 Capacity limitation

Limiting the number of refugee groups that a mobile clinic can serve at a node-time pair changes the optimal solution if constraint (14) in the MILP model becomes restrictive. Table C6 in Appendix C shows the best found solution by the MILP model for a maximum capacity C of when a run-time limit of 4 hours is still in place. Similarly, Table C7 shows the best found solution by the ALNS algorithm when eight runs are performed. The analysis is performed for values of C for which the capacity limit is restrictive for at least one instance, i.e. $C = 1, 2, 3, 4$. Figure 1 shows the average increase in objective value compared to the optimal objective value without a capacity limitation and Figure 2 shows the average number of mobile clinics used for different capacity limitations.

The ALNS model is again quickly able to find good solutions. We note that both the average increase in objective value and the number of clinics used is in all but one case higher for the MILP model. The higher values in the objective value are due to the run-time limit, since in some instances the optimal solution is not yet found and thus higher.

The total cost increases as the capacity limitation becomes more strict. From Figure 1 and Figure 2 we observe that both the average increase in the objective value and the number of mobile clinics used increase as C becomes smaller. Namely, as the capacity limit of mobile clinics decreases, on average more clinics need to be used. Moreover, the average increase in objective value as C decreases can be explained by an increase in fixed costs and by an increase in transportation costs. The former arises since more clinics are needed. The latter arises due to mobile clinics having to move to different nodes more often since combining the service of refugee groups at one node-time pair is restricted.

Further, we note that the average increase in objective value is 5 to 12 times higher for capacity limit $C = 1$ compared to capacity limit $C = 2$. This steep increase can partly be explained by the number of instances for which the capacity limit is restrictive. Namely, for $C = 2$ only 5 out of 25 instances experience an increase in objective value compared to the optimal objective value, whereas for $C = 1$ this holds for 16 out of 25 cases.

In line with this we observe that the introduction of a capacity limit has a large effect on the solution for low values of C. Specifically, for $C = 1$ the costs increase on average by 31% and 25% for the MILP model and ALNS algorithm respectively compared to no capacity limit. These are significant cost increases and the capacity limitation should therefore be taken into account in this problem. It is however hard to determine what values of C are realistic in this problem since this highly depends on the size of refugee groups, which is unknown in this network.

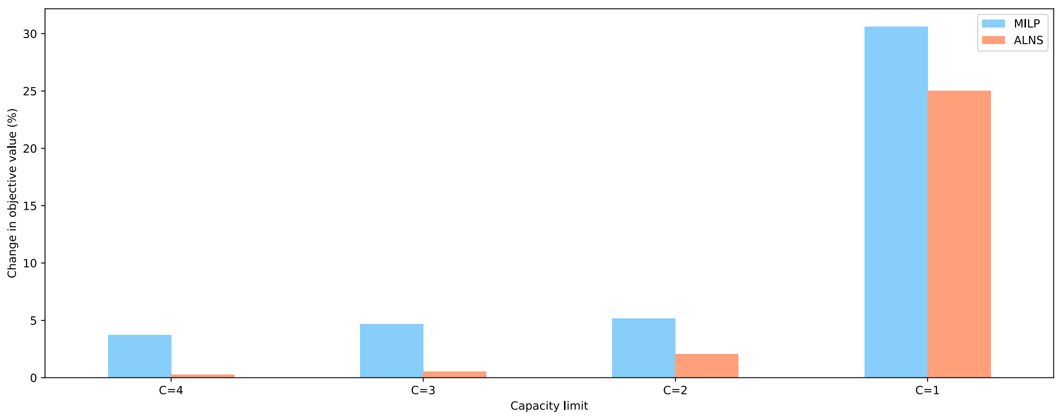


Figure 1. Average change in objective value for different capacity limitations for Honduras Migration Caravan Crisis

Note. The average is taken over all 25 instances listed in Table C1; the change in objective value is compared to the optimal solution without a capacity limitation.

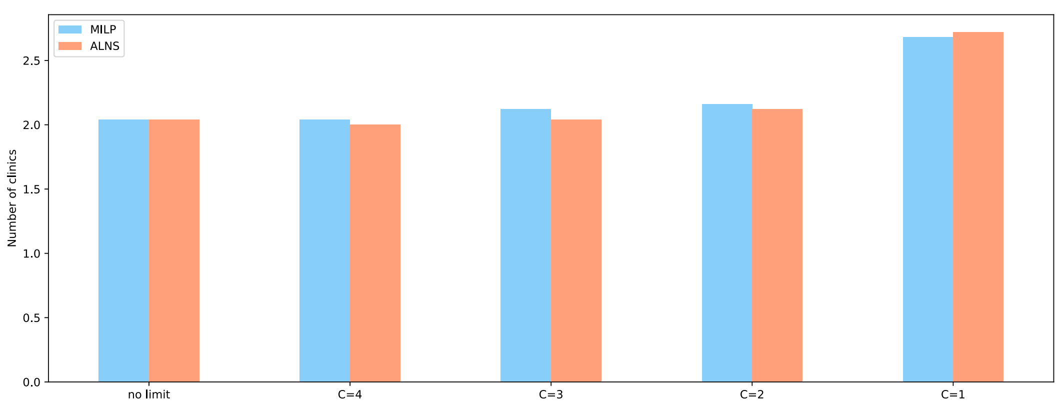


Figure 2. Average number of clinics used for different capacity limitations for Honduras Migration Caravan Crisis

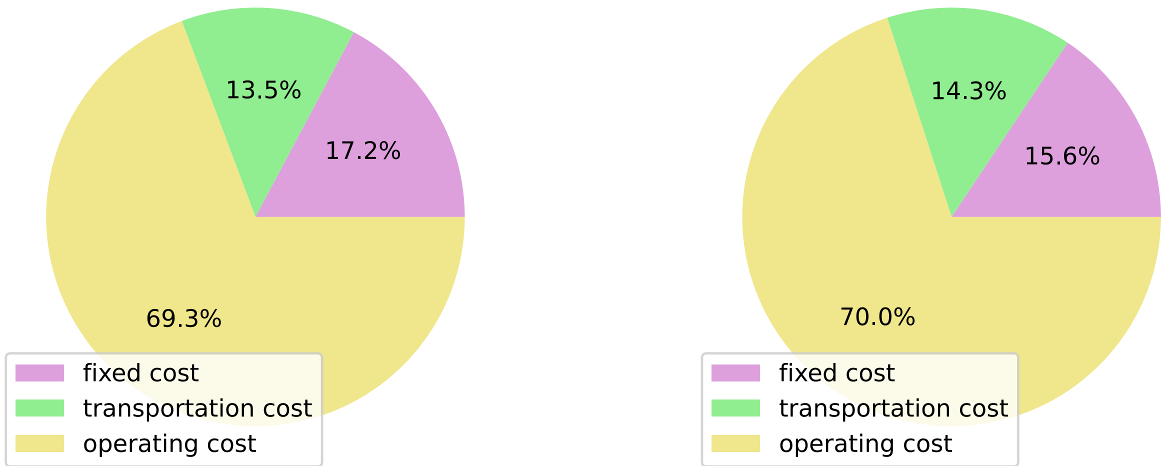
Note. The average is taken over all 25 instances listed in Table C1; *no limit* shows the average number of clinics used in the optimal solution without a capacity limitation.

5.1.5 Operating costs

The operating cost of serving a refugee group can be added to the model to minimize the number of services provided. Borderfree Association (2021) reports a monthly cost of 11500 CHF to operate one mobile clinic. We take the salary of the nurse and doctor as a fixed component and make the cost of medicine and treatment dependent on the number of days that a refugee group is already in transit. The variable costs increase with the number of days that a refugee group is in transit since they are exposed to bad living conditions that increase the probability of infections during their journey for longer. Namely, the fixed component is 1250 CHF and the variable component is constructed as $10000 * \frac{3}{4} * (1 + \frac{t-s}{|T|})$ CHF per month. Here, s denotes the number of the time period that the refugee group starts, t the number of the current time period and T the time horizon. By assuming there are 30.44 days in a month, the exchange rate is $1.03\frac{CHF}{€}$ and taking the unit travel cost as specified earlier, we can define the operating cost in terms of distance as $30+180*(1+\frac{t-s}{|T|})$km for one mobile clinic to serve a refugee group at period t.

If we include the operating cost of serving a refugee group into the objective function as described in Section 4.1.1, the value of the optimal objective changes and the number of service acts performed might change. Table C8 in Appendix C shows this change for each instance if the problem is solved using the MILP model. We again use a run-time limit of 4 hours. However, the limit on the optimality gap is set back to the default (0.001%) to ensure that the optimal solution is found when the run-time limit is not reached. Similarly, Table C9 shows the result of solving this version of the problem using the ALNS algorithm. Again, the table reports the best found solution when solving each instance eight times.

Including operating costs changes the optimal solution significantly. We observe that the objective value increases by on average 223.36% and 220.76% if operating costs are included using the MILP model and ALNS algorithm respectively. Note that the cost increase is slightly smaller for the ALNS algorithm due to the faster solving time. Moreover, the number of individual acts performed by a mobile clinic to one refugee group decreased by 13.46% and 13.38% when operating costs are included using the MILP model and ALNS algorithm respectively. The number of acts performed by a mobile clinic to a refugee group always decreased compared to the model without operating costs such that the number of service acts offered to a refugee group is minimized while still satisfying the service requirement.



(a) MILP model *(b)* ALNS algorithm

Figure 3. Average distribution total costs Honduras Migration Caravan Crisis with operating cost

It is important to incorporate operating costs into the problem in the future. The costs are realistic in practice and contribute a large extent to the total cost as can be seen from Figure 3. Not including these costs creates an unfair and unrealistic expectation for humanitarian organizations wanting to use mobile clinics to provide care to refugees in transit. Especially if the benefits of providing aid to refugees in transit are quantified to perform a cost-benefit analysis, the comparison between costs and benefits will otherwise be biased.

5.2 Western Balkan network

5.2.1 Data generation

The Western Balkan route is an important route to reach Western Europe for refugees coming from the Middle East, South-West Asia and Africa (Oruc et al., 2020). In 2015 to 2016 more than one million migrants took this route, but due to the border closure in 2016 this number started decreasing in the following years. However, the number of illegal border-crossing has been increasing again since 2019 and has more than doubled in 2021 according to Frontex (n.d.). For this reason, a dataset is constructed using the information on the Western Balkan route described by Šabić and Borić (2015). This report provides general information on how refugees move from one location to the next location. By combining this report with more detailed information on refugee camps along the route we were able to construct a detailed network of the Western Balkan route (Hameršak & Pleše, 2018; The Peace Institute, 2016; United Nations High Commissioner for Refugees, 2016).

The network consists of 19 nodes of which 11 can be reached by mobile clinics based on the size of the city or town represented by the node. Namely, we assume that the node can be reached by mobile clinics if the number of inhabitants is higher than 7000 or if there is a refugee camp at that node. Moreover, we again assume that the subnetwork of mobile clinics, G_ν, is complete. To determine the costs of mobile clinics in the Western Balkan Network, we again firstly determine the unit travel cost per kilometer. The fuel cost per kilometer is estimated at €0.54/km using the 2022 fuel prices in the Western Balkan region. Moreover, the cost of crossing borders is set to zero since crossing borders between the countries in the network is easy. Consequently, the fixed cost of using a mobile clinic in terms of distance is set to 1265km in this instance. Similar to the Honduras Migration Caravan Crisis network, the variable transportation costs are based on the shortest distance between nodes. Next, 12 different refugee paths are identified in the network following the information in Šabić and Borić (2015). The main path reaches from Idomeni (Macedonia) to Villach (Austria) (Figure D1). The time horizon is set to 20, such that 16 different refugee groups enter and leave the network. The required service frequency τ is set to 4 since there exists a path with three consecutive nodes where no mobile clinic can be located. Appendix D gives more detailed information on this network.

5.2.2 Results analysis

In this section, we present the results of using the MILP model and ALNS algorithm to solve the Western Balkan network. To solve the mathematical model we again use 0.01% as a limit on the optimality gap in CPLEX. For the ALNS algorithm, the same parameter values are used as in the Honduras Migration Caravan Crisis network.

Without changing the model and parameters, the MILP model and ALNS algorithm were quickly able to find the optimal solution. The optimal solution according to mobile clinics is shown in Table 4. Four mobile clinics are used in the optimal solution resulting in a fixed cost of 5060. Moreover, the transportation cost is 769 such that the optimal total cost is 5829. The MILP model is able to find the optimal objective value in 226 seconds. The ALNS algorithm found the optimal solution in all eight runs with an average running time of 15 seconds per run.

The utilization level is 45% for the Western Balkan network. Moreover, the service frequency is on average 0.32 received service acts per time period. Furthermore, using mobile clinics is in this instance again more efficient than using immobile clinics. We find that five clinics are needed if clinics are stationary and the total cost is thus 6325. The objective value decreases by 7.8% if mobile clinics are used compared to solving the model with immobile clinics.

Table 4. Optimal solution Western Balkan network mobile clinics

mobile clinic	**time period**																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1							15		15	15	18	18	17	17		17		17	17	
2			9		9		10	10	10	10		10		10	10			18		
3		2	2	2		2	2	2	2	2										
4					5	5	5		5	5	5	5	5							

Note. The table lists the nodes in which a service act is performed at the corresponding time period.

6 Conclusion

This paper analyzed the use of mobile clinics to provide basic health care to refugees in transit using data from the Honduras Caravan Migration Crisis and the Western Balkan route. The literature has shown that refugees in transit are at high risk of basic health problems and that regular access to health care is required to increase their health. Moreover, research has suggested that continuity of care is cost-effective, creating a positive economic impact. In this paper we therefore aimed to *determine the most efficient path of mobile health clinics for refugees in transit while guaranteeing a service frequency.*

To answer the research question, we defined *efficiency* in terms of cost and we set a minimum service requirement that differs per case. The MM-FLP-MD is presented and implemented using both a MILP model and an ALNS algorithm. The ALNS algorithm iteratively destroys and repairs the current solution with different operators to obtain a new solution. Moreover, a local search is performed every predetermined number of operations to improve the performance of the algorithm. Whereas the MILP model is not always able to find the optimal solution within 4 hours due to the $\mathcal{NP}$-hardness of the problem, the ALNS algorithm managed to find the optimal solution for all but two instances, taking at most 47 minutes to solve one instance. Moreover, we find that the optimal objective value found by the ALNS algorithm is in almost all instances better than the one found by the MILP model if a run-time limit is in place. Next to that, the running time is substantially lower for the ALNS algorithm than for the MILP model. From this we may conclude that the ALNS algorithm overcomes the $\mathcal{NP}$-hardness problem of the MILP problem and is an efficient method to find the optimal paths for mobile clinics to serve refugees in transit.

Furthermore, we added a capacity limitation to the MM-FLP-MD restricting the number of refugee groups a mobile facility can serve in a time period to bring the model closer to reality. The results show that when a mobile facility is restricted to be able to serve fewer refugee groups per time period, both the costs and number of mobile clinics used increase. This extension to the model also allowed us to include operating costs of providing aid to refugee groups in the model which minimizes the number of service acts offered while still satisfying the service requirement. For the Honduras Migration Caravan Crisis this reduced the number of individual service acts performed on average by approximately 13%. Thus, including operating costs in the objective function proves to be an effective method to limit the number of service acts provided by mobile clinics and consequently to reduce cost. The results also showed that it is important to add operating costs to the problem by looking at the cost distribution. Since operating costs are realistic in practice and account for around 70% of total costs, they should be included in the problem in the future.

Lastly, we showed that the model can be easily applied to different cases by solving the MM-FLP-MD for refugees in transit on the Western Balkan route. Without changing the parameters of the ALNS algorithm used for the Honduras Migration Caravan Crisis, the algorithm was able to find the optimal solution within 20 seconds. This shows that the algorithm is not case-specific and can be used for many different datasets.

To gain better insights on if and how mobile clinics should be used, further economic research should determine the cost-effect of guaranteeing continuity of care for refugees in transit. Moreover, the difference in the quality of health care provided by mobile clinics versus fixed facilities should be analyzed for refugees specifically. Next, looking at the assumptions of the model used in this paper, we note that refugee groups are assumed to be of equal size. This is however a simplification and a suggestion for further research is therefore to allow for different group sizes in the model. This will also enable a more precise formulation of capacity limitation and operating costs. Moreover, the paths and starting time periods of refugee groups are currently assumed to be deterministic. Including uncertainty in the model and thus allowing for stochastic refugee paths and starting times is an important next step to bring the model closer to reality.

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Appendix

A Algorithms

Algorithm 1 ALNS algorithm

Input: Initial solution s_0
$s \leftarrow s_0$
$s_{best} \leftarrow s_0$
$w_h \leftarrow \frac{1}{|R|}, \forall h \in R$ ▷ Initialize weight repair operation
$w_h \leftarrow \frac{1}{|D|}, \forall h \in D$ ▷ Initialize weight destroy operation
$iter \leftarrow 1$
while Stopping criterion not satisfied **do**
    if $iter \% \eta = 0$ **then** ▷ Weight adjustment
        $w_R \leftarrow adjust(w_R)$
        $w_D \leftarrow adjust(w_D)$
    end if
    if $iter \% \zeta = 0$ **then** ▷ Local search
        $s' \leftarrow LocalSearch(s)$
    end if
    $h_{repair} \leftarrow select(w_R)$ ▷ Select repair operation
    $h_{destroy} \leftarrow select(w_D)$ ▷ Select destroy operation
    $s' \leftarrow h_{repair}(h_{destroy}(s))$ ▷ Perform operations
    if $f(s') \leq f(s_{best})$ **then** ▷ Set new best solution
        $s_{best} \leftarrow s'$
    end if
    if $accept(s', s)$ **then** ▷ Set new solution for next iteration
        $s \leftarrow s'$
    end if
    $iter \leftarrow iter + 1$
end while
$s_{best} \leftarrow LocalSearch(s_{best})$ ▷ Local search on best solution
Output: s_{best}

Algorithm 2 Find set of minimal FSASs of time-indexed path π

```
Input: Time-indexed path $\pi(p, t)$
$\Phi_\pi \leftarrow \emptyset$
$\Phi'_\pi \leftarrow \emptyset$
for $i = 1$ to $\tau$ do
    if $a_{n(\pi(i))} = 1$ then                                ▷ Node in subnetwork of mobile clinics
        $\phi \leftarrow \emptyset$
        $\phi \leftarrow \phi \cup \{\pi(i)\}$
        $\Phi_\pi \leftarrow \Phi_\pi \cup \{\phi\}$
    end if
end for
while $\Phi_\pi \neq \emptyset$ do
    Pop first SAS $\phi$ from $\Phi_\pi$
    for $i = 1$ to $\tau$ do
        if $a_{n(\pi(t(\phi(|\phi|))-t+i+1))} = 1$ then          ▷ Node in subnetwork of mobile clinics
            $\overline{\phi} \leftarrow \phi \cup \pi(t(\phi(|\phi|)) - t + i + 1)$
            if $t(\overline{\phi}(|\overline{\phi}|)) - t(\overline{\phi}(|\overline{\phi} - 2|)) \leq \tau$ then      ▷ dominated FSAS
                Neglect $\overline{\phi}$
            else if $t(\overline{\phi}(|\overline{\phi}|)) + \tau - 1 \geq t(\pi(|\pi|))$ then      ▷ minimal FSAS
                $\Phi'_\pi \leftarrow \Phi'_\pi \cup \{\phi\}$
            else
                $\Phi_\pi \leftarrow \Phi_\pi \cup \{\phi\}$
            end if
        end if
    end for
end while
Output: $\Phi'_\pi$
```

B Description programming code

In this section we will provide a short description of the code in Java that is used to solve the MM-FLP-MD. The code is following the methods described in Section 4. The Java Project contains four Packages.

The Package *network* contains Classes to construct a network $G = (V, A)$. Classes represent (a set of) nodes, arcs, node-time pairs, paths, clinics or time periods. The network is used in the MILP model and ALNS algorithm.

Moreover, the Package *milp* contains one Class that consists of methods to create and solve the MM-FLP-MD using the MILP model. In this Class, the software package CPLEX is used. The Class creates the objective function and the constraints discussed in Section 4.1. Moreover, a method to solve the model and retrieve the optimal solution is added.

Next, the Package *alns* contains Classes to run the ALNS algorithm described in Section 4.2. The Class *Framework* contains all steps of Algorithm 1 and is able to display the results. Solutions are stored according to mobile clinics by storing their visit schedule and performed service acts, according to refugee groups by storing the node-time pairs they receive service and by storing the value of the objective function. Moreover, separate Classes containing all destroy- and repair operations are added containing operations discussed in Section 4.2.3 and Section 4.2.4 respectively. Different Classes for the framework, destroy operations and repair operations are created to add the capacity limitation and operating costs to the problem as discussed in Section 4.2.9. Finally, this package contains a Class representing the time-indexed path of a refugee group and an SAS received by a refugee group, which are both used in the ALNS algorithm.

Lastly, Package *instances* contains Classes to import the data and run the MILP model and ALNS algorithm for each instance. Classes *ImportingHonduras* and *Honduras* import and solve the MM-FLP-MD for the Honduras Migration Caravan Crisis in 2018 respectively. Classes *ImportingWB* and *WesternBalkan* import and solve the MM-FLP-MD for the Western Balkan route respectively. Moreover, the Package contains a Class that solves the MM-FLP-MD for a small test instance consisting of four refugee groups and six time periods that is presented by Bayraktar et al. (2022).

C Tables results

Table C1. Honduras Migration Caravan Crisis instances used

Name	$\|P\|$	$\|E\|$	$\|N\|$
P01E01N10_1	1	1	10
P01E02N10_1	1	2	10
P02E04N10_1	2	4	10
P02E04N10_2	2	4	10
P03E06N10_1	3	6	10
P03E06N10_2	3	6	10
P04E08N10_3	4	8	10
P04E08N10_4	4	8	10
P06E10N10_1	6	10	10
P06E10N10_2	6	10	10
P01E01N20_1	1	1	20
P01E02N20_1	1	2	20
P02E04N20_1	2	4	20
P02E04N20_2	2	4	20
P03E06N20_1	3	6	20
P03E06N20_2	3	6	20
P04E08N20_3	4	8	20
P04E08N20_4	4	8	20
P06E10N20_1	6	10	20
P06E10N20_2	6	10	20
P01E01N30_1	1	1	30
P01E02N30_1	1	2	30
P02E04N30_1	2	4	30
P02E04N30_2	2	4	30
P06E13N30_1	6	13	30

Table C2. Solution MILP model P06E13N30_1 mobile clinics

mobile clinic	**time period**																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1								19			14	15	16	14	15	20	15	14
2						6	6	10	9	9	11	11	11	11	11	11		
3			3	3	4	4	3	3		6	6	9	9	9	15	15		18
	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	
1	14	16	16	18	26	26		26				26	26					
2					18		21	21	23	23								
3	26	19	21	21	23	26		26		28				28	28			

Note. The table lists the nodes in which a service act is performed at the corresponding time period.

Table C3. Solution ALNS algorithm P06E13N30_1 mobile clinics

mobile clinic	**time period**																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1								19			14			18		20		
2			3	3		4	3	3		6	6	12	12	12	12	12	12	18
3						6	6	10	9	9	9	9	9	9	15	15	15	
	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	
1	26				26	26		26		28				28	28			
2	18			18	18	20	20											
3	15	15	21	21	23				23	23		26	26					

Note. The table lists the nodes in which a service act is performed at the corresponding time period.

Table C4. Solution MILP model P06E13N30_1 refugee groups

group	**time period**																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1	2	**3**	4	5	**6**	7	8	**9**	10	**11**	12	13	**14**	**15**	16	17	**18**
2					1	2	**3**	4	5	**6**	7	8	**9**	10	**11**	12	13	**14**
3						1	2	**3**	4	5	**6**	7	8	**9**	10	**11**	12	13
4					1	**4**	9	**19**	23	30								
5	1	2	**3**	4	5	**6**	9	**10**	11	12	**14**	**15**	**16**	18	19	**20**	21	23
6					1	2	**3**	4	5	**6**	9	10	**11**	12	14	**15**	16	**18**
7						1	2	**3**	4	5	**6**	**9**	10	**11**	12	14	**15**	16
8	1	2	**3**	4	5	**6**	7	8	**9**	10								
9		1	2	**3**	**4**	5	**6**	7	8	**9**	10							
10	1	2	**3**	4	5	**6**	7	8	**9**	10	**11**							
11		1	2	**3**	**4**	5	**6**	7	8	**9**	10	**11**						
12	1	2	**3**	4	5	**6**	7	8	**9**	10	**11**	12						
13		1	2	**3**	**4**	5	**6**	7	8	**9**	10	**11**	12					
	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	
1	19	20	**21**	22	**23**	24	25	**26**	27	**28**	29	30						
2	15	**16**	17	**18**	19	20	**21**	22	**23**	24	25	**26**	27	**28**	29	30		
3	**14**	15	**16**	17	**18**	19	20	**21**	22	**23**	24	25	**26**	27	**28**	29	30	
4																		
5	**26**	28	30															
6	19	20	**21**	23	**26**	28	30											
7	18	**19**	20	**21**	**23**	**26**	28	30										
8																		
9																		
10																		
11																		
12																		
13																		

Note. The table lists all nodes on the path; service is received at the nodes in bold.

Table C5. Solution ALNS algorithm P06E13N30_1 refugee groups

group	**time period**																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1	2	**3**	4	5	**6**	7	8	**9**	10	11	**12**	13	14	**15**	16	17	**18**
2					1	2	**3**	4	5	**6**	7	8	**9**	10	11	**12**	13	14
3						1	2	**3**	4	5	**6**	7	8	**9**	10	11	**12**	13
4					1	**4**	9	**19**	23	30								
5	1	2	**3**	4	5	**6**	9	**10**	11	12	**14**	15	16	**18**	19	**20**	21	23
6					1	2	**3**	4	5	**6**	**9**	10	11	**12**	14	**15**	16	**18**
7						1	2	**3**	4	5	**6**	**9**	10	11	**12**	14	**15**	16
8	1	2	**3**	4	5	**6**	7	8	**9**	10								
9		1	2	**3**	4	5	**6**	7	8	**9**	10							
10	1	2	**3**	4	5	**6**	7	8	**9**	10	11							
11		1	2	**3**	4	5	**6**	7	8	**9**	10	11						
12	1	2	**3**	4	5	**6**	7	8	**9**	10	11	**12**						
13		1	2	**3**	4	5	**6**	7	8	**9**	10	11	**12**					
	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	
1	19	20	**21**	22	**23**	24	25	**26**	27	**28**	29	30						
2	**15**	16	17	**18**	19	**20**	21	22	**23**	24	25	**26**	27	**28**	29	30		
3	14	**15**	16	17	**18**	19	**20**	21	22	**23**	24	25	**26**	27	**28**	29	30	
4																		
5	**26**	28	30															
6	19	20	**21**	23	**26**	28	30											
7	**18**	19	20	**21**	**23**	**26**	28	30										
8																		
9																		
10																		
11																		
12																		
13																		

Note. The table lists all nodes on the path; service is received at the nodes in bold.

Table C6. MILP model results Honduras Migration Caravan Crisis with capacity constraint

	capacity limitation							
	$C = 4$		$C = 3$		$C = 2$		$C = 1$	
Name	%Δ (1)	$\|m\|$	%Δ (1)	$\|m\|$	%Δ(1)	$\|m\|$	%Δ (1)	$\|m\|$
P01E01N10_1	0.00	1	0.00	1	0.00	1	0.00	1
P01E02N10_1	0.00	1	0.00	1	0.00	1	0.00	1
P02E04N10_1	0.00	1	0.00	1	0.00	1	0.00	1
P02E04N10_2	0.00	2	0.00	2	0.00	2	100.66	3
P03E06N10_1	0.00	2	0.00	2	0.00	2	24.48	3
P03E06N10_2	0.00	1	0.00	1	0.00	1	51.18	2
P04E08N10_3	0.00	2	0.00	2	0.00	2	21.57	3
P04E08N10_4	0.00	2	0.00	2	0.00	2	12.31	3
P06E10N10_1	0.00	3	0.00	3	0.00	3	9.08	4
P06E10N10_2	0.00	2	0.00	2	7.38	3	65.97	4
P01E01N20_1	0.00	1	0.00	1	0.00	1	0.00	1
P01E02N20_1	0.00	1	0.00	1	0.00	1	0.00	1
P02E04N20_1	0.00	2	0.00	2	0.00	2	0.00	2
P02E04N20_2	0.00	2	0.00*	2	0.00*	2	55.20*	4
P03E06N20_1	3.26*	2	0.00*	2	0.00*	2	27.66*	2
P03E06N20_2	0.00	2	0.00	2	0.00	2	25.42*	2
P04E08N20_3	6.56*	4	11.84*	4	0.00*	3	30.51*	3
P04E08N20_4	0.00*	3	0.00*	3	0.00*	3	15.23*	3
P06E10N20_1	3.73*	3	19.44 *	2	28.55*	4	71.23*	5
P06E10N20_2	2.50*	3	1.26 *	4	2.71*	3	53.39 *	4
P01E01N30_1	0.00	1	0.00	1	0.00	1	0.00	1
P01E02N30_1	0.00	1	0.00	1	0.00	1	0.00	1
P02E04N30_1	0.00	3	0.00	3	0.00	3	0.00	3
P02E04N30_2	4.27*	3	4.27*	3	4.27*	3	54.44*	3
P06E13N30_1	73.28*	3	80.15*	5	86.16*	5	147.76*	7
minimum	0.00	1	0.00	1	0.00	1	0.00	1
maximum	73.28	4	80.15	5	86.16	5	147.76	7
average	3.74	2.04	4.68	2.12	5.16	2.16	30.64	2.68

Note. %Δ (1) denotes the increase in objective function with respect to the optimal objective value; * denotes that the run-time limit is reached and the best found solution is reported.

Table C7. ALNS algorithm results Honduras Migration Caravan Crisis with capacity constraint

	capacity limitation							
	$C = 4$		$C = 3$		$C = 2$		$C = 1$	
Name	%Δ (1)	$\|m\|$	%Δ (1)	$\|m\|$	%Δ(1)	$\|m\|$	%Δ (1)	$\|m\|$
P01E01N10_1	0.00	1	0.00	1	0.00	1	0.00	1
P01E02N10_1	0.00	1	0.00	1	0.00	1	0.00	1
P02E04N10_1	0.00	1	0.00	1	0.00	1	0.00	1
P02E04N10_2	0.00	2	0.00	2	0.00	2	100.66	3
P03E06N10_1	0.00	2	0.00	2	0.00	2	24.48	3
P03E06N10_2	0.00	1	0.00	1	0.00	1	51.18	2
P04E08N10_3	0.00	2	0.00	2	0.00	2	21.57	3
P04E08N10_4	0.00	2	0.00	2	0.00	2	12.31	3
P06E10N10_1	0.00	3	0.00	3	0.00	3	9.08	4
P06E10N10_2	0.00	2	0.00	2	7.38	3	65.97	4
P01E01N20_1	0.00	1	0.00	1	0.00	1	0.00	1
P01E02N20_1	0.00	1	0.00	1	0.00	1	0.00	1
P02E04N20_1	0.00	2	0.00	2	0.00	2	0.00	2
P02E04N20_2	0.00	2	0.00	2	0.00	2	55.20	4
P03E06N20_1	0.00	2	0.00	2	0.00	2	15.09	2
P03E06N20_2	0.00	2	0.00	2	0.00	2	25.42	2
P04E08N20_3	0.03	3	0.03	3	0.03	3	19.76	3
P04E08N20_4	0.00	3	0.00	3	0.00	3	15.03	3
P06E10N20_1	1.09	3	1.93	3	1.93	3	62.33	5
P06E10N20_2	0.00	3	0.00	3	19.05	4	39.89	4
P01E01N30_1	0.00	1	0.00	1	0.00	1	0.00	1
P01E02N30_1	0.00	1	0.00	1	0.00	1	0.00	1
P02E04N30_1	0.00	3	0.00	3	0.00	3	0.00	3
P02E04N30_2	0.00	3	0.00	3	0.00	3	38.78	4
P06E13N30_1	5.90	3	11.70	4	23.88	4	69.42	7
minimum	0.00	1	0.00	1	0.00	1	0.00	1
maximum	5.90	3	11.70	4	23.88	4	69.42	7
average	0.28	2.00	0.55	2.04	2.09	2.12	25.05	2.72

Note. %Δ (1) denotes the increase in objective function with respect to the optimal objective value.

Table C8. MILP model results Honduras Migration Caravan Crisis with operating costs

Name	**optimal objective value**	**change %**	**optimal** $\lvert\phi\rvert$	**change %**
P01E01N10_1	1976	79.64	3	0.00
P01E02N10_1	2810	155.45	6	-14.29
P02E04N10_1	3486	157.08	8	-27.27
P02E04N10_2	4909	194.13	12	0.00
P03E06N10_1	4738	175.47	12	-14.29
P03E06N10_2	4536	234.51	12	-25.00
P04E08N10_3	5546	178.83	14	-33.33
P04E08N10_4	5576	180.20	14	-26.32
P06E10N10_1	7716	270.61	22	-26.67
P06E10N10_2	7841	276.61	22	-33.33
P01E01N20_1	3241	117.81	6	-14.29
P01E02N20_1	4944	231.37	12	-7.69
P02E04N20_1	5743	212.29	14	0.00
P02E04N20_2	7372	184.19	18	-5.26
P03E06N20_1	9570	228.87	25	-10.71
P03E06N20_2	8983	278.71	24	-14.29
P04E08N20_3	10257*	248.88	26	-10.34
P04E08N20_4	10216*	230.29	26	-10.34
P06E10N20_1	13418*	317.36	38	-11.63
P06E10N20_2	14311*	341.15	40	-20.00
P01E01N30_1	5108	139.92	10	-16.67
P01E02N30_1	8079	278.76	20	-4.76
P02E04N30_1	9681	235.80	24	0.00
P02E04N30_2	11729*	186.21	28	-3.45
P06E13N30_1	26937*	449.85	73	-6,49
minimum	1976	79.64	3	-33.33
maximum	26937	449.85	73	0.00
average	7948.92	223.36	20.36	-13.46

Note. Objectives are expressed in distance (km); *optimal objective value* is the best found objective value with a run-time limit; *change %* denotes the increase in objective function value and number of service acts compared to the optimal solution without the operating costs; * denotes that the run-time limit is reached and the best found solution is reported.

Table C9. ALNS algorithm results Honduras Migration Caravan Crisis with operating costs

Name	optimal objective value	change %	optimal $\|\phi\|$	change %
P01E01N10_1	1976	79.64	3	0.00
P01E02N10_1	2810	155.45	6	-14.29
P02E04N10_1	3486	157.08	8	-27.27
P02E04N10_2	4909	194.13	12	0.00
P03E06N10_1	4738	175.47	12	-14.29
P03E06N10_2	4536	234.51	12	-25.00
P04E08N10_3	5546	178.83	14	-33.33
P04E08N10_4	5576	180.20	14	-26.32
P06E10N10_1	7716	270.61	22	-26.67
P06E10N10_2	7841	276.61	22	-33.33
P01E01N20_1	3241	117.81	6	-14.29
P01E02N20_1	4944	231.37	12	-7.69
P02E04N20_1	5743	212.29	14	0.00
P02E04N20_2	7372	184.19	18	-5.26
P03E06N20_1	9570	228.87	25	-10.71
P03E06N20_2	8983	278.71	24	-14.29
P04E08N20_3	10258	248.91	26	-10.34
P04E08N20_4	10128	227.45	26	-10.34
P06E10N20_1	13381	316.21	38	-11.63
P06E10N20_2	14232	338.72	41	-18.00
P01E01N30_1	5108	139.92	10	-16.67
P01E02N30_1	8079	278.76	20	-4.76
P02E04N30_1	9681	235.80	24	0.00
P02E04N30_2	11728	186.19	28	-3.45
P06E13N30_1	24073	391,39	73	-6,49
minimum	1976	79.64	3	0.00
maximum	24073	391.39	73	0.00
average	7826.20	220.76	20.40	-13.38

Note. Objectives are expressed in distance (km); *optimal objective value* is the best found objective value when performing eight runs; *change %* denotes the increase in objective function value and number of service acts compared to the optimal solution without the operating costs.

D Western Balkan network data

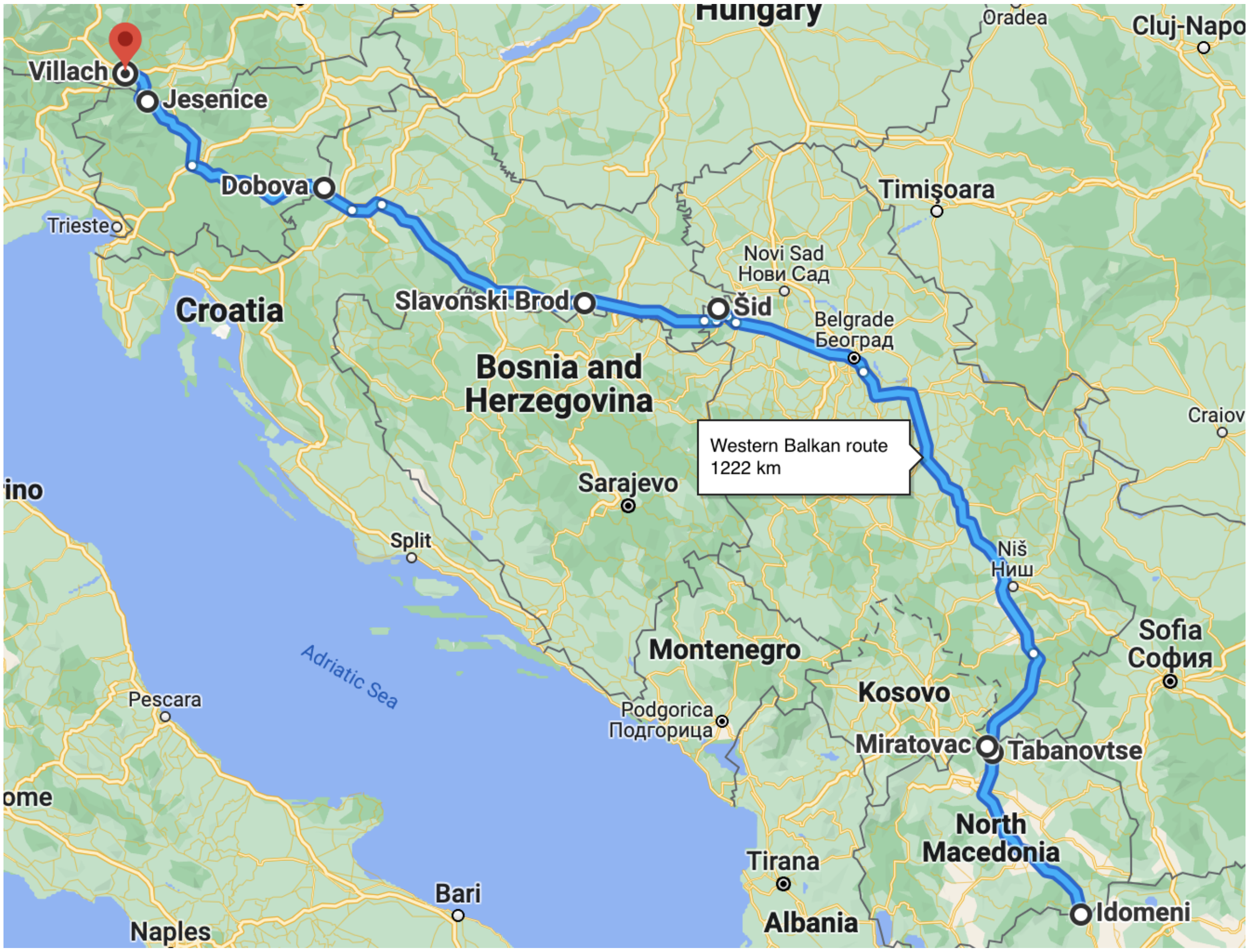

Figure D1. Main path Western Balkan route

Table D10. Western Balkan route node information

node	name	country	clinic node
1	Idomeni	Macedonia	no
2	Gevgelija	Macedonia	yes
3	Tabanovce	Macedonia	no
4	Miratovac	Serbia	no
5	Preševo	Serbia	yes
6	Dimitrovgrad	Serbia	yes
7	Zaječar	Serbia	yes
8	Belgrado	Serbia	yes
9	Šid	Serbia	yes
10	Slavonski Brod	Croatia	yes
11	Tovarnik	Croatia	no
12	Bapska	Croatia	no
13	Sibinj	Croatia	no
14	Mursko Središće	Croatia	no
15	Dobova	Slovania	yes
16	Rigonce	Slovania	no
17	Jesenice	Slovania	yes
18	Šentilj	Slovania	yes
19	Villach	Austria	yes

Table D11. Western Balkan route path information

path														
1	1	2	3	4	5	8	9	10	13	15	16	17	19	
2	1	2	3	4	5	8								
3	1	2	3	4	5	9	10	13	15	16	17	19		
4	1	2	3	4	5	8	9	11	10	13	15	16	17	19
5	1	2	3	4	5	8	9	12	10	13	15	16	17	19
6	1	2	3	4	5	8	9	10	13	14	16	18	19	
7	1	2	3	4	5	8	9	12	10	13	14	16	18	19
8	1	2	3	4	5	9	10	13	14	16	17	19		
9	6	8	9	11	10	13	15	16	17	19				
10	6	8	9	12	10	13	14	16	18	19				
11	7	8	9	10	13	15	16	17	19					
12	7	8	9	12	10	13	15	16	18	19				

Note. The table lists the nodes on the respective path.

Table D12. Western Balkan route refugee groups starting time periods

path	**time periods**		
1	1	5	7
2	5	8	
3	1		
4	1		
5	2		
6	1		
7	6		
8	3	9	
9	1		
10	3		
11	7		
12	1		

Note. time periods denotes the time periods in which a refugee group is starting on that path.

Table D13. Western Balkan route transportation cost

$i\backslash j$	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
1	0	13	172	181	186	340	430	556	661	756	668	683	767	1035	987	988	1147	1083	1182
2	13	0	163	172	177	424	420	547	651	747	659	674	758	1026	978	979	1138	1074	1173
3	172	163	0	8	15	262	311	385	490	585	497	512	596	864	816	817	976	912	1011
4	181	172	8	0	6	261	257	384	488	584	496	511	595	863	815	816	975	911	1010
5	186	177	15	6	0	259	255	383	487	582	494	510	593	861	813	814	973	909	1009
6	340	424	262	261	259	0	131	338	442	538	450	465	549	817	769	770	929	865	964
7	430	420	311	257	255	131	0	245	349	444	356	372	455	723	675	676	835	771	870
8	556	547	385	384	383	338	245	0	110	205	117	136	216	484	436	437	596	532	632
9	661	651	490	488	487	442	349	110	0	116	8	29	127	387	339	340	499	435	534
10	756	747	585	584	582	538	444	205	116	0	116	143	14	281	233	234	393	329	428
11	668	659	497	496	494	450	356	117	8	116	0	27	127	395	347	348	507	443	542
12	683	674	512	511	510	465	372	136	29	143	27	0	147	415	366	368	527	463	562
13	767	758	596	595	593	549	455	216	127	14	127	147	0	281	232	234	393	329	428
14	1035	1026	864	863	861	817	723	484	387	281	395	415	281	0	157	161	267	94	293
15	987	978	816	815	813	769	675	436	339	233	347	366	232	157	0	2	175	113	210
16	988	979	817	816	814	770	676	437	340	234	348	368	234	161	2	0	176	115	211
17	1147	1138	976	975	973	929	835	596	499	393	507	527	393	267	175	176	0	211	37
18	1083	1074	912	911	909	865	771	532	435	329	443	463	329	94	113	115	211	0	215
19	1182	1173	1011	1010	1009	964	870	632	534	428	542	562	428	293	210	211	37	215	0

Note. Costs are based on the shortest route in *km*.