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Innovative Applications of O.R.

Logistics planning of cash transfer to Syrian refugees in Turkey

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ABSTRACT

This paper addresses a humanitarian logistics problem connected with the Syrian refugee crisis. The ongoing conflict in Syria has caused displacement of millions of people. Cash-based interventions play an important role in aiding people in the post-crisis period to enhance their well-being in the medium and longer term. The paper presents a study on how to design a network of administrative facilities to support the roll-out of cash-based interventions. The resulting multi-level network consists of a central registration facility, local temporary facilities, mobile facilities and vehicles for door-to-door visits. The goal is to reach the maximum number of eligible beneficiaries within a specified time period while minimizing logistics costs, subject to a limit on total security risk exposure. A mixed integer programming model is formulated to optimize the inter-related facility location and routing decisions under multiple objectives. The authors develop a hierarchical multi-objective metaheuristic algorithm to obtain efficient solutions. An application of the model and the solution algorithm to real data from a region in the southeast of Turkey is presented, with associated managerial insights.

1. Introduction

Humanitarian assistance during disaster and crisis response is traditionally provided through distribution of in-kind goods and services. However, such in-kind support is increasingly criticized for its donor-driven nature and lack of offering long-term benefits for the beneficiaries (Haavisto & Kovács, 2014). Stories about lack of fit between in-kind support and local needs are abundant. The problems created by unsolicited in-kind aid, which may include for example inappropriate food and clothing or materials unfit for building shelter, are sometimes referred to as a “disaster after a disaster”. They can spoil and create logistical bottlenecks, and the cost of sorting, storing and distributing can even exceed the cash value of the donations (Ülkü, Bell, & Wilson, 2015). The humanitarian relief sector has therefore witnessed a shift towards a more prevalent use of *cash-based interventions* (CBIs) that replace or complement traditional in-kind assistance (Barrett, Bell, Lentz, & Maxwell, 2009). While CBIs are currently estimated to represent only around 6% of humanitarian spending (Hagen-Zanker, Ulrichs, & Holmes, 2018), many humanitarian agencies are actively working on increasing the proportion of CBIs in their operations, and identifying when and in which conditions cash-based approaches are preferable to the traditional in-kind assistance (Bailey, Savage, & O’Callaghan, 2008).

It is often argued that in-kind aid is preferable in the beginning phase of a crisis when markets and financial systems typically are disrupted or closed, while cash-based responses are more often used in later stages, both in the relief and recovery phases (Barrett et al., 2009; Doocy, Johnson, & Robinson, 2008; Mattinen & Ogden, 2006). Gairdner, Mandelik, and Moberg (2011) suggest that one reason for the growing interest towards CBIs is that the nature of the humanitarian crises has been changing to protracted and chronic crises rather than sudden onset, which may suit cash-based initiatives better.

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CBIs are appropriate when sufficient supplies of food and non-food needs are available in locally functional markets, yet a protracted crisis causes a decline in people's incomes and thus they are unable to meet their basic needs. Additional income received through CBI can then be helpful to support beneficiaries, provided local markets function. Likewise, in case of a sudden emergency and the recovery thereafter, CBIs can be applicable if supply is not interrupted or can be recovered quickly after the emergency (Bailey et al., 2008).

Cash based initiatives can be either unconditional or conditional to certain criteria, and can be transferred in different forms (i.e., modes), such as cash, vouchers, e-vouchers, or micro-credits. Delivery methods may vary as well, ranging from a direct delivery of cash or voucher by the humanitarian agencies or by subcontractors (often called cash-in-envelope method), cash payments at bank or post-office branches or at other widespread locations with public access, to payments into bank accounts or e-wallets accessed through ATM cards, Point-of-Sale (PoS) devices or mobile phones (Harvey, Haver, Hoffmann, & Murphy, 2010). Each of these mechanisms has its own requirements, advantages and disadvantages. Choosing the right delivery mechanism requires assessing the program requirements, user registration requirements, the capacity and capabilities of the financial service providers, security and controls, cost-efficiency and ease of implementation of the options (UNHCR, 2016).

If there is no financial infrastructure that can accommodate an agency's needs for implementing CBI or if the existing financial infrastructure is damaged by a crisis, agencies often distribute cash or vouchers physically to the beneficiaries. According to Harvey et al. (2010) the method of directly distributing cash in envelopes to the beneficiaries is then a commonly preferred one. This method has been used in several programs in Kenya, Niger, Southern Sudan, Vietnam, Mali and Bangladesh by organizations such as Save the Children, German Agro Action, Oxfam among others. Also, a number of delivery mechanisms are used together or in turn to assist the beneficiaries in the most timely and secure manner (Harvey et al., 2010). In one case in Lebanon where Syrian refugees were provided with cash-based shelter and winterization assistance, problems with the contracted bank resulted in a delay in the issuing of ATM cards. The implementing agency, International Organization for Migration (IOM), chose to proceed with a physical distribution of the vouchers for the first part of the program. This was executed by setting up distribution centers outside of the refugee settlements due to security concerns (IOM, 2015). In another case where IOM provided reparations for victims of the civil war in Sierra Leone, the main challenge of the program was that many of the beneficiaries resided in remote areas and the country had an underdeveloped banking system. As a solution, IOM contracted a local bank to set up mobile bank settlements on some specified days to issue payments to beneficiaries in remote areas. In a cash-based shelter assistance program in Pakistan, for every 25 families in remote regions a local representative was elected to do the distribution. These representatives were tasked with withdrawing the money from a bank branch and then physically distributing the money to the families in their group.

The logistics of such different forms of CBIs are not without challenges. The speed with which offices, staff and facilities have to be made available after a crisis to enable registration of CBI recipients and to handle the operations poses challenges (Doocy et al., 2008). The need to combine this high speed with high quality of response activities creates additional challenges (Heltberg, 2007). For example, eligible beneficiaries should be identified and registered to the cash transfer program as quickly and precisely as possible. In situations where electronic cards are the means of cash transfer, these cards should be distributed as soon as possible to beneficiaries, after which money can be transferred to the associated accounts. For example, Welt Hunger Hilfe (WHH), an organization which ran several e-voucher assistance programs for the Syrian refugees in southeastern Turkey in recent years, adopted physical distribution of vouchers as the delivery mechanism of the e-vouchers (WHH, 2016). WHH defines four main categories of physical distribution: centralized, localized, mobile and house-to-house distributions. In centralized distribution, beneficiaries (in the WHH situation this may be more than 1000) are invited to some central location; in this situation, the distribution phase can be completed in a few days. In localized distribution, distribution centers are established in regions/neighborhoods for typically one day only, and all beneficiaries in that neighborhood are then served within that same day. Mobile distribution facilities are parked in an area where beneficiaries can then pick up their vouchers; WHH uses this for up to around 50 families per day. For house-to-house distribution, the vouchers are delivered directly to the home addresses of the beneficiaries.

All of these operations require setting up administrative facilities in existing (typically public) buildings, or establishing temporary facilities somewhere close to the areas where the eligible beneficiaries reside. To serve rural areas large mobile facilities may be utilized, while remote and less populated areas may be reached by smaller vehicles. These different modes of service should be combined efficiently to reach the maximum number of beneficiaries in shortest possible time and at minimum logistics costs, while minimizing exposure to risky areas. Furthermore, the choice between these delivery mechanisms is based on trade-offs between the total cost of distribution, the time it takes to distribute all vouchers, the security of the agency employees and beneficiaries, and the total cost that beneficiaries must bear to collect their vouchers (travel, waiting, etc.).

Motivated by the increasing importance of CBIs in humanitarian operations, and inspired by the categorization of WHH and visits to the CBI programmes of amongst others IOM and UNHCR in Turkey, we investigate the design of a system to serve the recipients of a CBI program such that the delivery mechanisms mentioned above are combined in the most efficient and effective way. To this end, we propose a mathematical program that optimizes decisions on locating temporary facilities for localized distribution to support CBI, along with routing decisions for mobile and house-to-house distributions.

Our contributions are as follows: We analyze and model the logistics of registration and distribution in CBIs quantitatively for the first time in the humanitarian logistics (HL) literature. We propose a novel mathematical model for the registration/distribution problem that we pose as a bi-criteria covering location and two-modal multiple day routing problem with selected demand. We set our study in a slow-onset disaster, which is a type of disaster that is hardly studied in the literature. Last, we regard the efficiency of CBI logistics operations as well as their effectiveness. We maximize the funds available for direct distribution by allowing funds saved by reducing logistics costs to be passed on to the beneficiaries (e.g. via extra cash available to beneficiaries or indirectly). In the rest of this article, the terms "coverage" and "reach" have been used interchangeably, both referring to fulfillment of refugees' registration needs for the CBI scheme.

The remainder of this article is structured as follows. In the next section we provide a brief literature review both on humanitarian logistics and on cash-based interventions in order to specify where our work fills a gap in the literature. We then state our proposed mathematical model in Section 3, while the solution approach is discussed in Section 4. The numerical results of our case study are presented in Section 5 and finally the paper is concluded with future research directions in Section 6.

2. Literature review

2.1. Past research in Humanitarian logistics

In the past, numerous review papers have appeared that summarize research in HL. Below we refer to recent reviews that relate to our research objectives. Leiras, de Brito Jr, Queiroz Peres, Rejane Bertazzo, and Tsugunobu Yoshida Yoshizaki (2014) review 228 articles in HL and report that academia has focused on sudden-onset type of disasters. They conclude that man-made slow-onset disasters are the least studied type of disasters. They also identify that the response and preparedness are the most addressed stages of a disaster, while recovery is the least investigated one. In a similar vein, Chiappetta Jabbour et al. (2017) observe that researchers have studied more immediate responses than preparation and/or prevention events.

Özdamar and Ertem (2015) classify response and recovery-related research articles according to their optimization model structure type and functionality, and the solution approach. They argue that methods that can deal with large scale disasters efficiently are not readily available and that recovery in particular requires attention. Seifert, Kunz, and Gold (2018) discuss that quantitative application-oriented studies in this area are rather limited, and that none of those has managed to keep a well-maintained balance of focus between SCM aspects and refugee-related aspects. The authors conclude: “There is high potential for research on, e.g., SCM supporting refugees in long-established refugee camps. We suggest that future research should develop holistic and inclusive solutions for supply chain operations in connection with vulnerable persons and refugee camps”. Gupta, Starr, Farahani, and Matinrad (2016) state that “In humanitarian logistics, there is a need to have more integrated models that simultaneously take into account the location of distribution-centres, inventory positioning and distribution logistics”. They also point out that only half or less of the mathematical programming and decision analysis models in disaster management papers are based on real data. They therefore urge researchers to undertake case-based research in the field.

2.2. Cash based interventions

CBIs date back to 1990s when large-scale cash transfers were set up for refugee returnees in Central America as well as Afghanistan with more than 3.5 million beneficiaries, partly led by UNHCR. Similar schemes then were successfully used in several recovery operations around the world since then. Evidence of the effectiveness of CBI in humanitarian operations is limited but growing. Mattinen and Ogden (2006) report that CBI lead to much wider reach/coverage of beneficiaries compared to in-kind distribution, and is better able to achieve donors’ targets and to enhance beneficiaries’ dignity, particularly in complex emergencies and highly insecure environments.

Other researchers have widely studied the CBIs as an intervention that benefits the hosting community as well as the refugees (Hagen-Zanker et al., 2018). Davies and Davey (2008) reported the success of the cash transfer programme in Malawi by UNICEF, and its empowering impact on the local economy and small businesses/farms, with estimates that 1 dollar investment renders 2.02 to 2.45 times as much turnover in the local economy. Similar multiplier effects have been reported for CBI projects in the West Bank and Mexico (Harvey, 2005), and thus, Doocy, Tappis, and Doocy (2017) concluded an estimate of over $2 indirect market benefit for every $1 CBIs provided to the beneficiaries.

The main advantages of CBIs over in-kind aid can be categorised as follows:

1) *Social and economic development*: A recent, but growing body of literature has been extensively discussing and detailing the indirect impact of CBIs on higher levels of social and economic development. Such factors include, but are not limited to, stimulating the local economy (Doocy et al., 2017; Harvey, 2005; 2007), improving local security and cohabitation (Bailey, 2008), and cultural integration with the hosting community (Acheampong, 2015).
2) *Enhancement of the beneficiaries’ dignity*: The direct and indirect positive impact of CBI schemes on dignity of the beneficiaries have also been increasingly discussed in the humanitarian and disaster management literature. Factors discussed include social protection (Abu Hamad et al., 2017), poverty alleviation in general (Armstrong & Jacobsen, 2015), child poverty and child labour reduction (Barrientos & De Jong, 2006; De Janvry, Finan, Sadoulet, & Vakis, 2006)), reducing discrimination against, and manipulation of, the refugees (Berg, Mattinen, & Pattugalan, 2013)), employment rates among refugees (Creti, 2010), education (Abu Hamad et al., 2017), shelter and accommodation (Giordano, Dunlop, Sardiwal, & Gabay, 2017), physical health (Macours, Schady, & Vakis, 2008; UNHCR, 2012), mental health (Abu Hamad et al., 2017), dietary diversity and healthy nutrition (Doocy et al., 2017). Besides, receipt of regular cash support enables refugees to take the time/risk of searching for other livelihood opportunities or to go back to their home country/region once the crisis is over (Jacobsen & Fratzke, 2016).
3) *Enhancement of coping capabilities of beneficiaries*: Coping mechanisms are those choices that beneficiaries may exploit to cope with the refuge situations. Receiving cash via CBIs can reduce the beneficiaries’ need to restore harmful coping mechanisms such as selling critical assets by the beneficiaries (Hagen-Zanker et al., 2018). The positive impact of CBI schemes on the beneficiaries’ coping mechanisms also include work permit/opportunities (Acheampong, 2015), disposable income and debt repayments (Giordano et al., 2017), assets, livelihood and investments (Bastagli et al., 2016; ECHO, 2009).
4) *Enhancing the performance of the donors and humanitarian organisations*: Donors and humanitarian organisations are important stakeholders of CBI schemes and typically have related targets to achieve and report on. In fact, the use of CBI schemes can improve donors’ own performance measures, including cost efficiency (Doocy et al., 2017), overall coverage and equality (UNHCR, 2012), aid distribution speed (Berg et al., 2013), beneficiaries’ satisfaction (Uekermann & M., 2017), staff and beneficiary safety (Sandvik, Jumbert, Karlsrud, & Kaufmann, 2014). CBI schemes have also been reported to reduce the risk of fraud and corruption in operations (Doocy et al., 2008).

CBIs are not entirely risk-free, and a few challenges and limitations have been reported for such schemes. There is a risk of transferring cash to conflict zones to support fighters, exemplified by several cases where ex-combatants in African countries had benefited from CBIs (Willibald, 2006). CBI programmes have also been blamed in many cases for leading to inflation in local markets and to rising cost of living (REACH, 2015). Besides, tension with host communities has been reported occasionally as an indirect negative effect of CBIs aimed at beneficiaries (Jacobsen, 2002; Long, 2010). Rise of unemployment rates and housing prices are reported to be one of the primary issues that lead to tensions between the host community and CBI receivers (Washington & Rowell, 01 Apr 2013). Therefore, CBIs not only require a stable and non-disrupted infrastructure, preferably designed in addition to in-kind support, but they also require carefully targeting to avoid negative impacts on beneficiaries and hosting communities. Mattinen and Ogden (2006) explain that the key to a successful CBI scheme is a clear set of CBI objectives, target beneficiaries, and appropriate employed modalities. This highlights the need for an effective and efficient supply chain that supports cash-based interventions. In fact, supply chain management for CBI (referred to as CBI-SCM) has been raised recently as one the main challenges in humanitarian operations, needing more academic research (Seifert et al., 2018).

Before diving into the details of the supply chain challenges of CBIs we first describe the case study that we aim to analyse.

2.3. CBI for Syrian refugees

According to the United Nations Refugee Agency, as of January 2019, 64% of the 5,663,664 registered Syrian refugees are living in Turkey, from whom more than 90% live outside refugee camps and within cities and towns in the country (see UNHCR, 2019).

Distributing e-cards/vouchers to the Syrian refugees in Turkey first started mid-October 2012 in five refugee camps. WFP launched a programme to distribute food vouchers by the World Food Programme (WFP), in partnership with the Turkish Red Crescent Society (TRC). An unconditional, unrestricted cash assistance programme was later on carried out by the Danish Refugee Council (DRC) via the Turkish post office (PTT) in 2014. However, this programme was limited to supermarket e-cards given to vulnerable families after some time due to administrative and contractual issues that prevented continuation with the PTT partnership (Armstrong & Jacobsen, 2015). After the successful experience of cash assistance programmes in Lebanon, the EU Humanitarian Aid set up a partnership with the WFP, TRC and the Turkish government for the Emergency Social Safety Net (ESSN) programme. Under this programme, every eligible household was to be provided with a debit card, used to transfer multi-purpose monthly cash electronically to the cardholder. The programme launched in December 2016, scaled up to cover more than 1 million refugees beyond 2018 and it is reportedly the biggest humanitarian project that the EU has ever funded. During the lifetime of the project, there were yet several million cards to be distributed to the Syrian refugees in Turkey, which represents a colossal challenge in managing the supply chain of CBI distribution.

The focus of this paper is on registration and distribution challenges of the unconditional form of CBIs. Such challenges fall into two main categories: location-related challenges (ensuring security, limiting diversion, solving supply and technology related issues) and programme or agency-related challenges (reaching target groups, ensuring maximum coverage, and realizing minimum distribution time). Ensuring security of both recipients and distributors is deemed to be one of the most prominent challenges of CBIs. Security risk depends on the mode of cash transfer, and is significantly mitigated when cash and vouchers are replaced with bank cards and e-vouchers (Sabates-Wheeler & Devereux, 2010; Sandvik et al., 2014). We focus on the location-related challenges.

Below we first summarize the relevant facility location and distribution model literature before presenting our model.

2.4. Facility location and relief aid distribution models

In the HL literature, studies on relief network design have mainly focused on locating facilities such as response centers, warehouses, and points of distribution, combined with the transportation of goods (e.g., Rawls & Turnquist, 2010). Some studies, in addition, address the last mile distribution of goods (e.g., Afshar & Haghani, 2012; Rath & Gutjahr, 2014), and others also incorporate the amount of commodities to be stocked (e.g., Tofighi, Torabi, & Mansouri, 2016). Anaya-Arenas, Renaud, and Ruiz (2014) review studies on the design of relief distribution networks in response to disasters, including those that integrate facility location and relief commodity distribution decisions. Here we discuss the most relevant studies which propose mathematical models that combine facility location and commodity distribution to demand points.

Afshar and Haghani (2012) propose a mathematical model to optimize the flow of relief commodities through the supply chain and address decisions related to vehicle routing and pick up and delivery schedules, as well as locations for hierarchies of temporary facilities. Rath and Gutjahr (2014) propose a mathematical model with three objectives to locate warehouses and to distribute relief commodities originating from these warehouses. Their model decides on the location of depots, assignment of aid recipients to the depots, and routes to serve the recipients. Wang, Du, and Ma (2014) address the distribution of relief items in post-disaster response and combine distribution center location and routing decisions with split deliveries. They consider three objectives, including maximization of the minimum route reliability, and propose two heuristics for the solution of the model. Saffarian, Barzinpour, and Kazemi (2017) propose a multi-objective model for location and routing of vehicles under uncertainty. Ni, Shu, and Song (2018) optimize facility location, inventory pre-positioning, and relief delivery decisions in the pre-disaster preparedness stage by a robust optimization approach. However, the second-stage delivery decisions involve flow of the commodity rather than its distribution by vehicle routing. Vahdani, Veysmoradi, Noori, and Mansour (2018) also followed a robust optimization approach, this time for a two-phase, multi-objective mixed integer, multi-period and multi-commodity mathematical model for a three-level relief chain design.

Ferrer et al. (2018) note that in last mile distribution of relief aid, several conflicting objectives need to be considered together. The authors furthermore point out that security is an increasingly important criterion to optimize in operations that are carried out in environments of armed conflict and social unrest. In line with this statement, security risk is one of the objectives we consider in our model. Talarico, Sörensen, and Springael (2015b) have introduced a variant of risk-constrained routing problem inspired by cash-in-transit vehicles and proposed a mathematical model based on additive measuring of risk on routes. In a different approach to avoid risk in case of unforeseen circumstances, Talarico, Sörensen, and Springael (2015a) have developed a k-dissimilar vehicle routing problem to generate a set of feasible alternative routes with a certain level of distinction, characterized by edges in common among routes. They have used a min-max design to minimize the cost of the worst route in the solution set.

We remark here that location-routing problems have many different applications in commercial supply chains. A recent such example is the design of used product networks by Hosseini, Deghanian, and Salari (2019). In that application, vehicles visit customers to collect used products which is also selective location-routing problem application since the company may choose not to collect the used product depending on the profit. Motivated by a real life application, Rahim and Sepil (2014) provide another example, namely the glass recycling problem. In that study the location of bottle banks and the daily routes of the vehicles are determined. Such examples are prevalent in other commercial supply chains. We note that a comprehensive review of studies on location-routing problems is provided by Prodhon and Prins (2014) and Drexl and Schneider (2015). We refer the interested reader to these papers and the references therein.

3. Problem statement and mathematical model

In our problem setting, we focus on the registration and distribution of the e-voucher cards (e.g. KizilayKart) among beneficia-

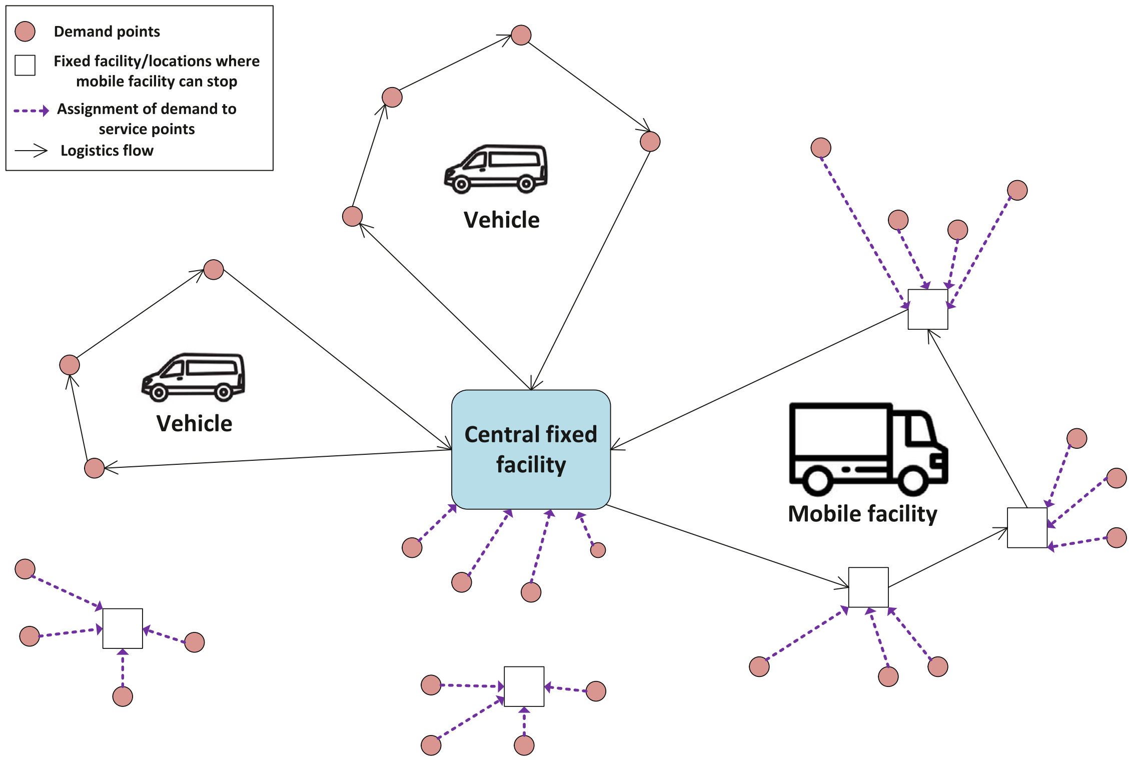


Fig. 1. Schematic illustration of the supply network.

ries. These activities can take place: (i) in a central facility, (ii) in temporary facilities, (iii) in a mobile facility, and (iv) through vehicles (see Fig. 1). We assume these activities need to be accomplished within a predetermined planning horizon.

The locations of the beneficiaries are aggregated to the centroids of neighbourhoods and villages, the smallest provincial administrative units in Turkey. These locations constitute the demand points to be served by the facilities and the vehicles.

The central facility, which could be a municipality building, is the base of operations. Its location is a high level decision and is not made within our model. It has the capacity to serve all the demand points within a given radius, hence those demand points are excluded from further analysis.

In contrast with the central facility, we can decide on the location of the temporary facilities, which may be located in buildings owned and operated by the government. In practice, the candidate locations for temporary facilities are hospitals and schools. The temporary facilities serve the demand points within a radius, with a daily capacity of beneficiaries it can serve per day. We assume that the temporary facilities are provided by the government in a given number at no cost, which is in line with current practice in Turkey.

The distribution operation utilizes a single mobile facility, a container-based office carried by a trailer, which is loaded at the central facility at the beginning of the planning horizon and must return to the central facility before the end of the planning horizon. Similar to the temporary facilities, it can serve demand points within a radius and has a daily capacity. It must be located in one of the candidate locations for each day, and can spend more than a day in any of its stops to serve more beneficiaries. The candidate locations for its stops are usually a subset of the candidate locations for the temporary facilities, and in practice, consist of the locations of the schools in the area.

An investigation by Oxfam showed that people walk on average 3.7 miles for fetching water (Oxfam, 2019). World Economic Forum research shows that hospitals in several countries in Africa are about a 2 h walk away (WEF, 2018) and Wong, Benova, and Campbell (2017) show that pregnant women in their study lived about 15 km away from a health facility. We assume people will travel further than that distance for registration and they will travel up to a distance of 20 km, which set the limit for the reach of the temporary facilities and the mobile facility.

We also operate a fleet of vehicles that start and end their tours at the central facility. The vehicles serve each demand point through direct visits, whereas the temporary facility and mobile facility can serve demand points at a distance. Each vehicle follows a daily schedule and should return back to the central facility by the end of each day.

Employing the mobile facility and the vehicles incur a daily fixed cost in addition to a variable cost proportional to the distance traveled. The routes of the mobile facility and vehicles are subject to a maximum risk level that should not be exceeded for the sake of security.

Within this setting, the decisions to make are:

1. where to locate temporary facilities among the candidate locations,
2. which of the candidate locations should be visited using the mobile facility and in which sequence, and how long should the mobile facility stay at each location,
3. which demand points should be visited using a vehicle and the corresponding routes of the vehicles,
4. to which facilities should the unvisited demand points be assigned to.

3.1. Summary of assumptions

- Refugees are registered using any of the following four ways: (1) a central facility, (2) any of the temporary facilities, (3) a mobile facility that travels between candidate service locations,

(4) vehicles that can visit any demand point (and thus can provide door-to-door service).

- Candidate locations for the temporary facilities are known.
- A single mobile facility and K vehicles are available.
- Demand points can not be covered/reached via a combination of different facilities.
- All demand in a demand point should either be served completely during the planning horizon or not served at all (partial coverage per node is not allowed to avoid conflict among refugees).
- A demand point may be served by only a single type of facility but not their combination, and their coverage per visit can be partial. For instance, serving one third of a demand point per day during three days will ensure its complete coverage.
- Each facility has a predetermined hourly service rate.
- The mobile facility starts its routes at the central facility, stops at each candidate location one or more days before visiting the next candidate location. At the end of the planning horizon, it returns to the central facility.
- Vehicles also start their routes from the central facility and return to the central facility at the end of each day.
- Employing the mobile facility or a vehicle incurs a fixed daily cost ($f^{(2)}$, $f^{(3)}$) in addition to a variable cost ($c_{ij}^{(2)}$, $c_{ij}^{(3)}$) proportional to the traveled distance.
- The feasible coverage radius to assign the demand points to each facility is 20 km.
- Daily travel time plus service time for each of the vehicles should not exceed daily working hours.
- The mobile facility cannot visit multiple locations per day.

Our two objectives are (1) to maximize demand coverage and (2) to minimize the total logistics cost. As such, we aim not only to address the efficiency of the operation, but also consider its effectiveness by targeting maximum fulfillment of demand. We first introduce the notation in Table 1, after which we propose a mathematical programming model in (2)–(29) which represents a location-routing problem.

$$\text{(EVCHR)}\quad \max \sum_{j\in\mathcal{D}} b_j\left[\sum_{i\in\mathcal{F}:j\in\mathcal{S}_i^{(1)}} Z_{ji}^{(1)} + \sum_{i\in\mathcal{P}:j\in\mathcal{S}_i^{(2)}} Z_{ji}^{(2)} + \sum_{i\in\mathcal{D}:j\in\mathcal{S}_i^{3}} Z_{ji}^{(3)}\right], \tag{1}$$

$$\min \sum_{i\in\mathcal{P}} f^{(2)}U_i^{(2)} + \sum_{(i,j)\in\mathcal{E}^{(2)}} c_{ij}^{(2)}X_{ij}^{(2)} + \sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}}\left[f^{(3)}U_{kt}^{(3)} + \sum_{(i,j)\in\mathcal{E}^{(3)}} c_{ij}^{(3)}X_{ktij}^{(3)}\right], \tag{2}$$

s.t.

$$\sum_{i\in\mathcal{F}:j\in\mathcal{S}_i^{(1)}} Z_{ji}^{(1)} + \sum_{i\in\mathcal{P}:j\in\mathcal{S}_i^{(2)}} Z_{ji}^{(2)} + \sum_{i\in\mathcal{D}:j\in\mathcal{S}_i^{(3)}} Z_{ji}^{(3)} \le 1, \qquad j\in\mathcal{D}, \tag{3}$$

$$Z_{ji}^{(1)} \le Y_i^{(1)}, \qquad i\in\mathcal{F},\, j\in\mathcal{D}\cap S_i^{(1)}, \tag{4}$$

$$\sum_{i\in\mathcal{F}} Y_i^{(1)} \le p, \tag{5}$$

$$\sum_{j\in S_i^{(1)}} Z_{ji}^{(1)} b_j \le \theta|\mathcal{T}|r^{(1)}, \qquad i\in\mathcal{F}, \tag{6}$$

$$Z_{ji}^{(2)} \le Y_i^{(2)}, \qquad i\in\mathcal{P},\, j\in\mathcal{D}\cap S_i^{(2)}, \tag{7}$$

$$\sum_{(i,j)\in\delta^{(2)}(0)} X_{ij}^{(2)} \le 2, \tag{8}$$

$$\sum_{(i,j)\in\delta^{(2)}(m)} X_{ij}^{(2)} = 2Y_m^{(2)}, \qquad m\in\mathcal{P}, \tag{9}$$

$$\sum_{(i,j)\in\delta^{(2)}(S)} X_{ij}^{(2)} \ge 2Y_m^{(2)}, \qquad S\subset\mathcal{P}\cup\{0\} : 0\in S,\, m\in\mathcal{P}\backslash S, \tag{10}$$

$$\ln(1-\bar{\alpha}) \le \sum_{(i,j)\in\mathcal{E}^{(2)}} \ln(1-\alpha_{ij})X_{ij}^{(2)}, \tag{11}$$

$$\sum_{j\in S_i^{(2)}} Z_{ji}^{(2)} b_j \le r^{(2)} I_i^{(2)}, \qquad i\in\mathcal{P}, \tag{12}$$

$$\sum_{i\in\mathcal{P}} I_i^{(2)} \le |\mathcal{T}|\theta, \tag{13}$$

$$I_i^{(2)}/\theta \le U_i^{(2)}, \qquad i\in\mathcal{P}, \tag{14}$$

$$Z_{ji}^{(3)} \le \sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} Y_{kti}^{(3)}, \qquad i\in\mathcal{D},\, j\in\mathcal{D}\cap S_i^{(3)}, \tag{15}$$

$$\sum_{(i,j)\in\delta^{(3)}(0)} X_{ktij}^{(3)} \le 2, \qquad k\in\mathcal{K},\, t\in\mathcal{T}, \tag{16}$$

$$\sum_{(i,j)\in\delta^{(3)}(m)} X_{ktij}^{(3)} = 2Y_{ktm}^{(3)}, \qquad k\in\mathcal{K},\, t\in\mathcal{T},\, m\in\mathcal{D}, \tag{17}$$

$$\sum_{(i,j)\in\delta^{(3)}(S)} X_{ktij}^{(3)} \ge 2Y_{ktm}^{(3)}, \qquad k\in\mathcal{K},\, t\in\mathcal{T},\; S\subset\mathcal{D}\cup\{0\} : 0\in S,\, m\in\mathcal{P}\backslash S, \tag{18}$$

$$\ln(1-\bar{\alpha}) \le \sum_{(i,j)\in\mathcal{E}^{(3)}} \ln(1-\alpha_{ij})X_{ktij}^{(3)}, \qquad k\in\mathcal{K},\, t\in\mathcal{T}, \tag{19}$$

$$\sum_{(i,j)\in\mathcal{E}^{(3)}} \tau_{ij}X_{ktij}^{(3)} + \sum_{i\in\mathcal{D}} I_{kti}^{(3)} \le \theta, \qquad k\in\mathcal{K},\, t\in\mathcal{T}, \tag{20}$$

$$I_{kti}^{(3)} \le \max\{\theta, \frac{b_i}{r^{(3)}}\}Y_{kti}^{(3)}, \qquad k\in\mathcal{K},\, t\in\mathcal{T},\, i\in\mathcal{D}, \tag{21}$$

$$\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} I_{ktj}^{(3)} \ge \frac{b_j}{r^{(3)}} \sum_{i\in\mathcal{D},\, j\in S_i^{(3)}} Z_{ji}^{(3)}, \qquad j\in\mathcal{D}, \tag{22}$$

$$Y_{kti}^{(3)} \le U_{kt}^{(3)}, \qquad k\in\mathcal{K},\, t\in\mathcal{T},\, i\in\mathcal{D}, \tag{23}$$

$$Z_{ji}^{(1)}, Y_i^{(1)} \in \{0,1\}, \qquad i\in\mathcal{F},\, j\in\mathcal{D}, \tag{24}$$

$$Z_{ji}^{(2)}, Y_i^{(2)} \in \{0,1\}, U_i^{(2)} \in \mathbb{Z}_+, \qquad i\in\mathcal{P},\, j\in\mathcal{D}, \tag{25}$$

$$Z_{ji}^{(3)}, Y_{kti}^{(3)}, U_{kt}^{(3)} \in \{0,1\}, \qquad k\in\mathcal{K},\, t\in\mathcal{T},\, i,j\in\mathcal{D}, \tag{26}$$

$$X_{ij}^{(2)} \in \{0,1\}, \qquad i,j\in\mathcal{P}\cup\{0\}, \tag{27}$$

Table 1
Definition of the sets, parameters and variables.

Symbol	Definition
	Sets
$\mathcal{T}$	Time periods of the planning horizon: $\{1,\ldots,T\}$
$\mathcal{F}$	Set of candidate locations for temporary facilities
$\mathcal{P}$	Set of candidate locations for the mobile facility to stop and serve
$\mathcal{D}$	Set of demand points
$\mathcal{N}$	$\mathcal{N}=\mathcal{F}\cup\mathcal{P}\cup\mathcal{D}\cup\{0\}$, where 0 denotes the central facility
$\mathcal{K}$	Set of vehicles $\quad \mathcal{K}=\{1,2,\ldots,K\}$
$\mathcal{E}^{(2)}$	Set of edges of a complete undirected graph defined on $\mathcal{P}\cup\{0\}$
$\mathcal{E}^{(3)}$	Set of edges of a complete undirected graph defined on $\mathcal{D}\cup\{0\}$
$\mathcal{S}_i^{(1)}\subseteq\mathcal{D}$	Set of demand points which can be served by a temporary facility at location $i\in\mathcal{F}$
$\mathcal{S}_i^{(2)}\subseteq\mathcal{D}$	Set of demand points which can be served by the mobile facility at location $i\in\mathcal{P}$
$\mathcal{S}_i^{(3)}\subseteq\mathcal{D}$	Set of demand points that can be served by the vehicle at location $i\in\mathcal{D}$
$\delta^{(2)}(S)$	Set of edges with one end in S and the other in $(\mathcal{P}\cup\{0\})\backslash S$
$\delta^{(3)}(S)$	Set of edges with one end in S and the other in $(\mathcal{D}\cup\{0\})\backslash S$
	Parameters
$f^{(2)}$	Fixed daily cost of using the mobile facility
$f^{(3)}$	Fixed daily cost of using a vehicle
$c_{ij}^{(2)}$	Transportation cost of the mobile facility travelling from location i to j
$c_{ij}^{(3)}$	Transportation cost of a vehicle travelling from location i to j
τ_{ij}	Transit time of a vehicle between locations i and j
b_i	Beneficiary population at location $i\in\mathcal{D}$
θ	Daily amount of time (hours) facilities are in service
α_{ij}	Risk of a security incident on arc (i,j) of a route, where $\alpha_{ij}<1$
$\bar{\alpha}$	Maximum acceptable risk on a route, where $\bar{\alpha}\leq 1$
$r^{(1)}$	Per hour service rate of a temporary facility
$r^{(2)}$	Per hour service rate of the mobile facility
$r^{(3)}$	Per hour service rate of a vehicle
	Decision variables
$Y_i^{(1)}$	1 if a temporary facility is opened at location $i\in\mathcal{F}$; 0, otherwise
$Y_i^{(2)}$	1 if the mobile facility visits location $i\in\mathcal{P}$; 0, otherwise
$Y_{kti}^{(3)}$	1 if vehicle $k\in\mathcal{K}$ visits location $i\in\mathcal{D}$ on day $t\in\mathcal{T}$; 0, otherwise
$I_i^{(2)}$	Amount of time the mobile facility stays at location $i\in\mathcal{P}$
$I_{kti}^{(3)}$	Amount of time vehicle $k\in\mathcal{K}$ serves in demand point $i\in\mathcal{D}$ on day $t\in\mathcal{T}$
$U_i^{(2)}$	Number of days the mobile facility is used in location $i\in\mathcal{P}$
$U_{kt}^{(3)}$	1 if the vehicle $k\in\mathcal{K}$ is used on day $t\in\mathcal{T}$; 0, otherwise
$X_{ij}^{(2)}$	1 if the mobile facility k moves from location i to location j at the end of day t; 0, otherwise
$X_{ktij}^{(3)}$	1 if the vehicle $k\in\mathcal{K}$ travels from $i\in\mathcal{D}\cup\{0\}$ to location $j\in\mathcal{D}\cup\{0\}$ on day $t\in\mathcal{T}$; 0, otherwise
$Z_{ji}^{(1)}$	1 if location $j\in\mathcal{D}$ is served by a temporary facility at location $i\in\mathcal{F}$; 0, otherwise
$Z_{ji}^{(2)}$	1 if location $j\in\mathcal{D}$ is served by the mobile facility at location $i\in\mathcal{P}$; 0, otherwise
$Z_{ji}^{(3)}$	1 if location $j\in\mathcal{D}$ is served by vehicles visiting $i\in\mathcal{D}$; 0, otherwise

$$X_{ktij}^{(3)}\in\{0,1\},\qquad k\in\mathcal{K},t\in\mathcal{T},i,j\in\mathcal{D}\cup\{0\},\tag{28}$$

$$I_i^{(2)}\geq 0,\qquad i\in\mathcal{P},\tag{29}$$

$$I_{kti}^{(3)}\geq 0,\qquad k\in\mathcal{K},t\in\mathcal{T},i\in\mathcal{D}.\tag{30}$$

The objective function (1) maximizes the total reach while (2) minimizes total logistics cost. Constraint (3) ensures that each identified demand point should be served at most once. Constraints (4), (7) and (15) correspond to the opening of a temporary facility, visit of the mobile facility and vehicles to the service points, respectively. The number of temporary facilities to be set up is bounded above by p, as stated in constraint set (5).

The model takes into account the capacity of temporary facilities, the mobile facility and the vehicles respectively by constraints (6), (12) and (21), respectively.

Constraint sets (8)–(10) ensure that the mobile facility leaves the central facility at most once, visits each location at most once, and every location it visits is connected to the central facility.

Constraints (11) and (19) are the linearized forms of the maximum acceptable risk on a route. Note that by using the generic edge traversal variables $X_{ij}^{(2)},X_{ktij}^{(3)}\in\{0,1\}$, the probability of no incidents happening on edge (i,j) can be computed as $(1-\alpha_{ij})^{X_{ij}^{(.)}}$. Assuming independence of the probabilities of incidents, the probability that an unwanted event occurs on the whole route, consisting of edge set A, is $\prod_{(i,j)\in A}(1-\alpha_{ij})^{X_{ij}^{(.)}}$. Hence, the constraint can be stated as $1-\prod_{(i,j)\in A}(1-\alpha_{ij})^{X_{ij}^{(.)}}\leq\bar{\alpha}$or equivalently,

$$1-\bar{\alpha}\leq\prod_{(i,j)\in A}(1-\alpha_{ij})^{X_{ij}^{(.)}}\tag{31}$$

which is equivalent to (11) and (19) by applying the natural logarithm to both sides of (31) and replacing the corresponding variables $X_{ij}^{(2)}$ and $X_{ktij}^{(3)}$ with $X_{ij}^{(.)}$. We can easily exclude edges with $\alpha_{ij}=1$ from the network or set $X_{ij}^{(.)}=0$ for them. Hence, we have not included such cases in the model.

Constraint sets (13) and (20) limit the staying time of the mobile facility and vehicles in the visited locations, respectively.

Constraint sets (16)–(18) correspond to daily routing of each vehicle in such a way that each vehicle leaves the central facility at most once each, visits each location at most once whereas each location it visits is connected to the central facility.

Constraint (22) imposes the minimum staying time of each vehicle at each visited location to cover all demand while (23) detects whether a vehicle is used in a particular day or not. Finally, constraint sets (24)–(30) define the type of decision variables.

We now demonstrate the relationship between our method of modeling risk with that of Talarico et al. (2015b). The authors define a parameter ν_{ij} to denote the vulnerability of arc (i, j), corresponding to the probability that an attack on this arc results in a robbery, which can be computed based on historical data. In addition, they define D_i^r as the amount of physical loss due to a successful attack on any arc that departs from location i on route r. Consequently, the authors compute the risk of a route $r = ((0, i), (i, j), \ldots, (k, 0))$ in an additive manner as $\alpha_{0i}\nu_{0i}D_0^r + (1-\alpha_{0i})\alpha_{ij}\nu_{ij}D_i^r + \ldots + (1-\alpha_{0i})(1-\alpha_{ij})(\ldots)\alpha_{k0}\nu_{k0}D_k^r$.

We emphasize that our problem is a one-time distribution problem, for which there cannot be any historical data, so we can safely assume that ν_{ij} is constant and equal for all arcs. Note that Talarico et al. (2015b) employ the same assumption in their paper. In addition, the amount of physical loss D_i^r is also a constant and equal for all locations and all routes in our case, due to the fact that we plan the distribution of cards rather than cash and they have no value unless registered and validated. Based on these two observations, we prove below that our multiplicative method of computing the risk is equivalent to the one of Talarico et al. (2015b).

Proposition 3.1. *For ν_{ij} being constant and equal for all arcs (i, j), and D_i^r being constant and equal for each route r and location i, the additive and multiplicative methods of computing risk return identical results.*

Proof. Let us start by defining the probability of no-incident on arc (i, j) as $\bar{\alpha}_{ij} = 1 - \alpha_{ij}$, for the sake of brevity. Then, we can state the risk of route $r = ((0, i), (i, j), \ldots, (k-2, k-1), (k-1, k), (k, 0))$ multiplicatively as $(1 - \bar{\alpha}_{0i}\bar{\alpha}_{ij})\ldots\bar{\alpha}_{k-1,k}\bar{\alpha}_{k0}$. Under the constant vulnerability and loss assumption stated above, the parameters ν_{ij} and D_i^r can be factored out, and the risk of the route can be additively computed as the sum:

$$\begin{aligned}
&1-\bar{\alpha}_{0i}+\\
&\bar{\alpha}_{0i}(1-\bar{\alpha}_{ij})+\\
&\ldots\\
&\bar{\alpha}_{0i}\,\bar{\alpha}_{ij}\,\ldots\,\bar{\alpha}_{k-2,k-1}\,(1-\bar{\alpha}_{k-1,k})+\\
&\bar{\alpha}_{0i}\,\bar{\alpha}_{ij}\,\ldots\,\bar{\alpha}_{k-1,k}\,(1-\bar{\alpha}_{k0})
\end{aligned} \tag{32}$$

Expanding the products we get

$$\begin{aligned}
&1-\bar{\alpha}_{0i}+\\
&\bar{\alpha}_{0i}-\bar{\alpha}_{0i}\,\bar{\alpha}_{ij}+\\
&\ldots\\
&\bar{\alpha}_{0i}\,\bar{\alpha}_{ij}\,\ldots\,\bar{\alpha}_{k-2,k-1}\,-\bar{\alpha}_{0i}\,\bar{\alpha}_{ij}\,\ldots\,\bar{\alpha}_{k-2,k-1}\bar{\alpha}_{k-1,k}+\\
&\bar{\alpha}_{0i}\,\bar{\alpha}_{ij}\,\ldots\,\bar{\alpha}_{k-2,k-1}\,\bar{\alpha}_{k-1,k}\,-\bar{\alpha}_{0i}\,\bar{\alpha}_{ij}\,\ldots\,\bar{\alpha}_{k-1,k}\,\bar{\alpha}_{k0}
\end{aligned} \tag{33}$$

Observe that the second term in each line cancels out the first term of the following line, except for the last line. This results in a total of $1 - \bar{\alpha}_{0i}\bar{\alpha}_{ij}\ldots\bar{\alpha}_{k-1,k}\bar{\alpha}_{k0}$, which is equal to the result of the multiplicative method. □

As a final remark, we state that the multiplicative method suits our purposes better since it yields to the logarithmic linearization method.

4. Solution approach

Routing models are computationally difficult for optimization packages and therefore, strengthening them may significantly reduce the computation time and lead to obtaining better solutions within a limited time. In the following we first propose two valid inequalities for strengthening our mathematical model. Then, as large instances of the problem are still computationally intensive, we also propose a sequential heuristic algorithm which maximizes the reach with minimum logistics cost.

4.1. Strengthening the model

4.1.1. The connectivity constraints

The routing part of our mathematical model is capacitated. However, the capacity in our model is characterized by the available working time rather than physical specifications of the vehicle or facilities. Therefore, vehicles should not visit the central facility multiple times on a working day, provided that the triangular inequality holds for the distance matrix. In other words, the mobile facility or each vehicle (per day) has at most one route. This fact allows us to replace inequalities (8) and (15) with their stronger counterparts in the form of the equality as described in the following remark.

Remark 1. Routing constraints:

(a) $\mathbf{X_1} = \{X_{ij}^{(2)} : \sum_{(i,j)\in\delta(0)} X_{ij}^{(2)} = 2W; W \geq X_{ij}^{(2)}, \forall (i, j) \notin \delta(0); W \in \{0, 1\}\}$ is a stronger connectivity constraint set than (8).

(b) $\mathbf{X_2} = \{X_{ij}^{(3)} : \sum_{(i,j)\in\delta(0)} X_{ijt}^{(3)} = 2W_t; W_t \geq X_{ij}^{(3)}, \forall (i, j) \notin \delta(0); W_t \in \{0, 1\}\}$ is a stronger connectivity constraint set than (15).

For the sake of brevity only part (a) is proved below. A similar argument can be followed for part (b).

Proof. Let $\mathcal{Q}$ be the set of $X_{ij}^{(2)}$ variables on which (8) holds. Then it suffices to show that $\mathbf{X_1} \subset \mathcal{Q}$. Now let $\tilde{W}, \tilde{X}_{ij}, \forall (i, j) \in \tilde{\mathcal{E}} \subseteq \mathcal{E}^{(2)}$ be an arbitrary element of $\mathbf{X_1}$. Then, $\sum_{(i,j)\in\delta(0)} \tilde{X}_{ij}^{(2)} = 2\tilde{W} \leq 2$. Therefore, $\tilde{x}_{ij}, \forall (i, j) \in \mathcal{Q}$ and thus, $\mathbf{X_1} \subseteq \mathcal{Q}$. Now, consider a solution with $\bar{W} = 0$ and a set of $\bar{X}_{ij}^{(2)}, \forall (i, j) \in \mathcal{E}^{(2)}$ such that $\sum_{(i,j)\in\delta^{(2)}(0)} \bar{X}_{ij}^{(2)} = 0$ and $\bar{X}_{ij} = 1$ for $(i, j) \notin \delta^{(2)}(0)$. Obviously it belongs to $\mathcal{Q}$ but not to $\mathbf{X_1}$. That is, $\mathbf{X_1} \nsubseteq \mathcal{Q}$ and therefore, $\mathbf{X_1} \subset \mathcal{Q}$. □

The above stated alternative sets of constraints were driven by observing many sub-tour elimination iterations in our preliminary numerical studies. When feeding the original model to the solver it struggles to eliminate many intermediate infeasible solutions whose infeasibilites arise from not being connected to the central facility rather than having several sub-tours. Therefore, using $\mathbf{X_1}$ and $\mathbf{X_2}$ prevents such solutions and leads to a significant reduction of computation time.

4.1.2. Symmetry breaking constraints

The combination of days and vehicles within the planning horizon does not have an effect on coverage, as vehicles are the same and there is no timing priority among the nodes. Therefore, to avoid such a symmetry due to the presence of the same vehicles at each day, we added the following constraints

$$U_{k,t}^{(3)} \geq U_{k,t+1}^{(3)}, \quad k \in \mathcal{K}, t \in \mathcal{T} \tag{34}$$

$$U_{k,t}^{(3)} \geq U_{k+1,t}^{(3)} \quad k \in \mathcal{K}, t \in \mathcal{T}. \tag{35}$$

This simple lexicographical symmetry breaking constraints significantly improve the computational time by reducing the search space.

4.2. Initial solution construction and improvement approach

The proposed optimization model is decomposable with respect to the first objective function. That is, by relaxing (3), three sub-problems respectively composed of: {(4)–(6)}, {(7)–(14)}, and {(15)–(23)} can be solved independently. Therefore, we have used them to obtain an initial solution for EVCHR through a process described in Algorithm 1. It starts with maximizing the reach only by solving a facility location problem for the temporary facilities via CPLEX optimizer. Having fixed them, a routing problem is then solved for the mobile facility to maximize covering the remaining demand. Next, the heuristic constructs the routes to reach unvisited locations as much as possible in a greedy way. Finally, an iterative local search is applied to improve the costs by keeping the realized reach. In other words, having obtained the objective value obj_1^* in the reach maximization problem, the following constraint is added to the model in transition to the cost minimization problem.

$$\sum_{i\in V_c\setminus(\mathcal{H}\cup\mathcal{L})} r_i \left[\sum_{m\in\{1,2,3\}} \sum_{j\in V_c: i\in S_j^{(m)}} z_{ij}^{(m)} \right] \geq obj_1^*. \tag{36}$$

Note that as discussed in subsection 4.1.1, in an optimal solution each vehicle has at most one tour and therefore, given the set of visited nodes for each vehicle and day, the optimal route can be obtained by solving a Traveling Salesperson Problem (TSP). In addition, since the number of nodes visited daily by each vehicle is small due to working time limitations, it is practical to exactly optimize each individual route by applying a dynamic programming algorithm for the TSP. Thus, we have equipped our local search with only an inter-route 2-Exchange operator. However, as the visited nodes within the route also have associated service times and multiple visits of a node are allowed, exchanging nodes between routes is not a simple swap. Rather, depending on the length of service times, and existence of the same node as candidate nodes in candidate routes, different situations can happen as illustrated in Fig. 2. We refer to this exchange as *Exchange** within Algorithm 1. As shown, only when service times are equal and no common node exists, this exchange is reduced to a conventional simple swap (see case B.3 in Fig. 2).

Algorithm 1 Obtaining an initial solution from sub-models.

Input: Problem parameters (locations, costs, populations).
Output: A feasible solution for (EVCHR).

Solve the location sub-model resulting from dropping $Z_{ij}^{(2)}, Z_{ij}^{(3)}$ from objective 1) and maximizing it subject to {(4)–(6)} and $\left\{\sum_{i\in\mathcal{F}: j\in S_i^{(1)}} Z_{ji}^{(1)} \geq 1\right\}$ to determine the locations of the temporary facilities
$\bar{Z}_{ij}^{(1)} \leftarrow$ obtained $Z_{ij}^{(1)}$
Solve the vehicle routing sub-model resulting from dropping $Z_{ij}^{(1)}, Z_{ij}^{(3)}$ in objective (2) and maximizing it subject to {(7)–(14)} and $\left\{\sum_{i\in\mathcal{F}: j\in S_i^{(2)}} \bar{Z}_{ji}^{(2)} + \sum_{i\in\mathcal{D}: j\in S_i^{(3)}} Z_{ji}^{(3)} \geq 1\right\}$
$\bar{Z}_{ij}^{(2)} \leftarrow$ obtained $Z_{ij}^{(2)}$
Construct a sorted list of the remaining demand nodes $i \in \mathcal{D}$ in descending order of distance weighted population values, i.e. $b_i \times d_{0i}$.
  //CONSTRUCTION OF INITIAL VEHICLE ROUTES:
Set the required time of each demand node i to $b_i/r^{(3)}$
for $t \in \mathcal{T}$ **do**
  for $k \in \mathcal{K}$ **do**
    Initialize service time, transit time, and risk of the route of vehicle k on day t to 0
    while (sum of service and transit times $\leq \theta$) **and** (route risk $\leq \alpha$) **do**
      Insert the first demand node in the sorted list with positive required time to the end of the route
      Compute the service time spent at the inserted node, as the minimum of the remaining time on the route, and required time of the node
      Update required time at the node by subtracting the service time spent
      Update the service time, transit time, and risk of the route
    end while
    Optimize the route using the Dynamic Programming (DP) algorithm of Held and Karp (1962).
  end for
end for
  //IMPROVING VEHICLE ROUTES:
Initialize $NoImp \leftarrow 0$
repeat ▷ Local Search
  for $(t_1, k_1) \in \mathcal{T}\times\mathcal{K}$ **do** ▷ first route
    for $(t_2, k_2) \in \mathcal{T}\times\mathcal{K}$ **do** ▷ second route
      if $(t_1, k_1) \neq (t_2, k_2)$ **then**
        for each pair of nodes, one from each route **do**
          *Exchange** the nodes, and apply DP to the routes
          if (the objective value improves) and (the new solution is feasible) **then**
            update best known solution
            $NoImp \leftarrow 0$
          else
            $NoImp \leftarrow NoImp + 1$
          end if
        end for
      end if
    end for
  end for
until $NoImp < MaxNoImprv$

5. Case study

In our case study, we work on data from the province of Kilis that is located in the southeastern part of Turkey. Kilis has a population of 121,566 residents, and reportedly, 123,029 Syrian refugees were piloted. Based on our analysis of the data, we have identified 18 potential service points (3 hospitals and 15 schools), and 187 demand points (109 villages and 78 neighborhoods) as illustrated in Fig. 3.

The parameters corresponding to these locations, and all instances and solutions on which our numerical results in the rest of this section are based, are available at https://doi.org/10.17632/36y25cbbx8.3.

The transportation costs between each pair of locations have been set proportional to their distance based on the fuel consumption estimate of the mobile facility and vehicles, while their daily fixed costs are set based on their daily rental fare in Turkey. That is, $f^{(2)}$=500 and $f^{(3)}$=100, while $c_{ij}^{(2)}$ and $c_{ij}^{(3)}$ were obtained by multiplying d_{ij} by 0.5 and 0.75, respectively. The maximum acceptable risk is considered as 5% and the per hour service rate of each temporary facility, the mobile facility and vehicles are set as $r^{(1)} = 60$, $r^{(2)} = 12$ and $r^{(3)} = 8$, respectively. The total working time per day is 10 hours for each facility. Thus, to cover at least 80% of beneficiaries in a single run, we have considered several combinations of the planning horizon length (T) and number of temporary facilities (p) and number of vehicles (K) which characterize the nominal capacity as described in the following subsection.

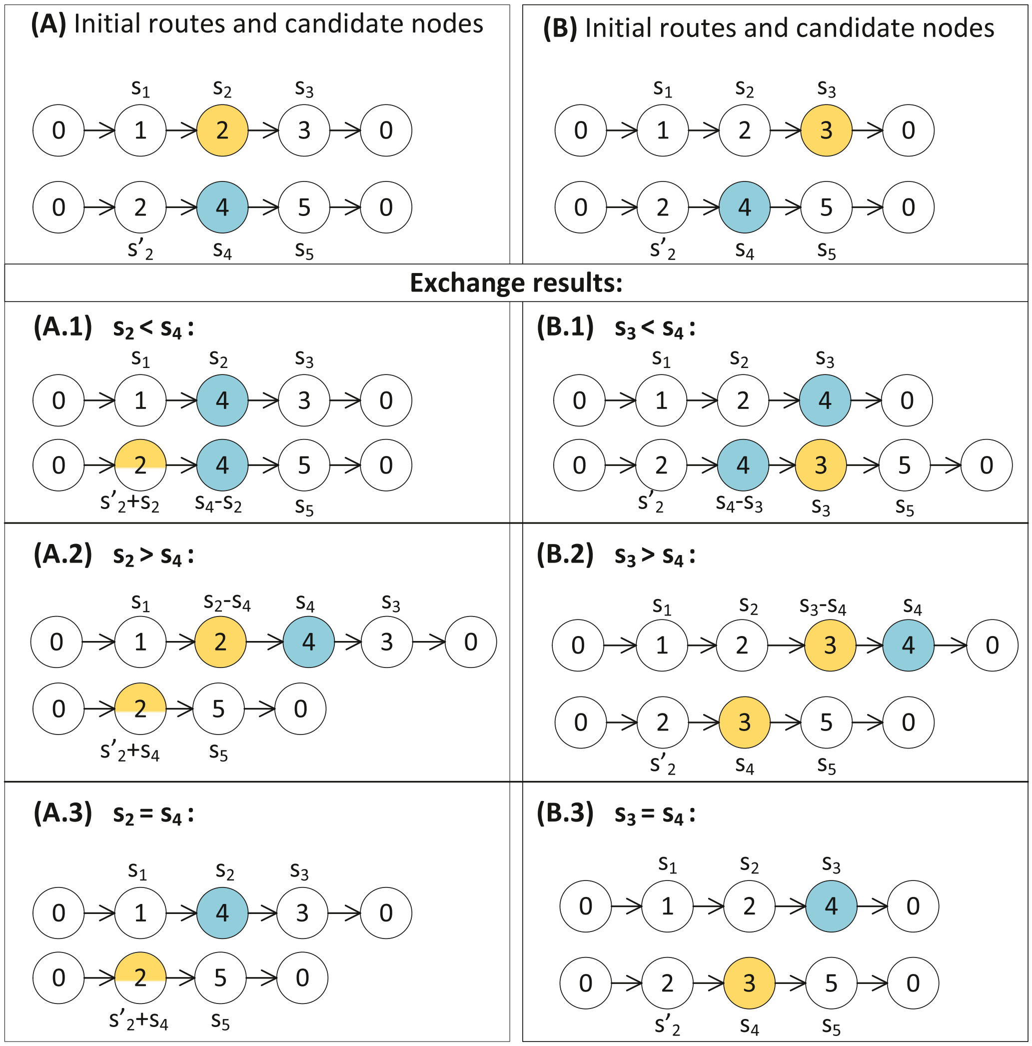
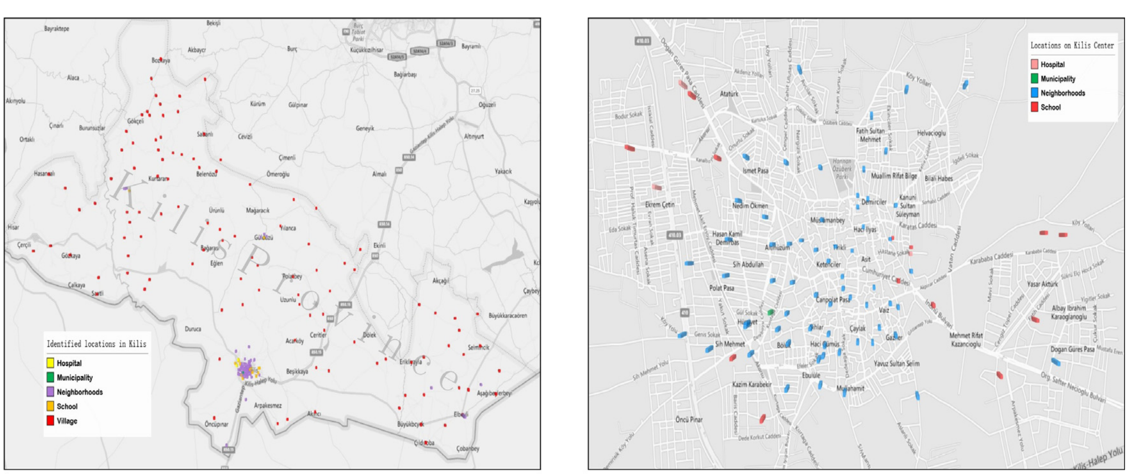


Fig. 2. *Exchange** operator illustration: each row includes the sequence of nodes within the routes. Candidate nodes are colored and the service times are written above and below the nodes.



(a) Kilis province (b) Kilis center

Fig. 3. Region map and the classified locations.

Table 2
The nominal capacities (in %) corresponding to pairs of (T, p) having 10 vehicles.

Planning Horizon (T)	Allowed number of temporary facilities (p): 8	9	10	11	12	13	14	15	16	17	18
7	47.2	52.2	57.1	62.1	67.0	72.0	76.9	81.9	86.8	91.8	96.7
8	53.9	59.6	65.3	70.9	76.6	82.2	87.9	93.6	99.2	104.9	110.5
9	60.7	67.1	73.4	79.8	86.2	92.5	98.9	105.2	111.6	118.0	124.3
10	67.4	74.5	81.6	88.7	95.7	102.8	109.9	116.9	124.0	131.1	138.2
11	74.2	82.0	89.7	97.5	105.3	113.1	120.9	128.6	136.4	144.2	152.0
12	80.9	89.4	97.9	106.4	114.9	123.4	131.8	140.3	148.8	157.3	165.8
13	87.7	96.9	106.1	115.2	124.4	133.6	142.8	152.0	161.2	170.4	179.6
14	94.4	104.3	114.2	124.1	134.0	143.9	153.8	163.7	173.6	183.5	193.4

Capacity groups: A B C D E F G

Table 3
Average statistics of the obtained solutions over capacity groups.

CG	Cap	T	p	K	Reach	Cost	Risk	TF%	MF%	V%	nTF	nMF	nV	nRT
A	85.10	9.9	11.9	5.3	84.5	11901.0	0.046	78.61	1.40	4.54	119.1	5.1	27.3	51.4
B	94.91	10.2	12.9	5.6	90.1	13577.0	0.048	84.04	1.43	4.59	135.8	5.9	27.1	54.5
C	104.98	10.6	13.5	5.6	91.3	14164.5	0.048	85.03	1.50	4.76	137.3	6.4	26.9	56.9
D	114.78	11.2	13.9	5.5	91.9	14746.1	0.049	85.43	1.58	4.91	137.4	6.2	27.5	58.9
E	124.52	11.6	14.5	5.7	92.6	15458.4	0.049	85.69	1.64	5.23	141.1	6.1	27.7	62.5
F	134.51	12.0	15.2	5.6	93.0	15737.0	0.049	85.97	1.69	5.31	141.6	6.4	27.1	63.3

'CG': capacity group; 'Cap':nominal capacity; 'T': planning horizon (days); 'p': number of temporary facilities; 'K': number of vehicles; 'Reach': % of registered refugees; 'TF%': contribution of tixed facilities; 'MF%': contribution of the mobile facility; 'V%': contribution of vehicles; 'nTF': number of nodes served by temporary facilities; 'nMF': number of nodes visited by mobile facility; 'nV': number of nodes visited by vehicles; 'nRT': number of routes; 'Imp%': cost improvement of reach maximization mode; 'time': total computational time (s)

5.1. Capacity configurations

Each of the temporary facilities can register $r^{(1)}$ people per hour, while the service rate of the mobile facility and each vehicle are $r^{(2)}$ and $r^{(3)}$ people per hour, respectively. In other words, given p temporary facilities and K vehicles, the nominal registration capacity of the system over a T-day planning horizon which serves θ hours per day is $T\theta\left(r^{(1)}p + r^{(2)} + r^{(3)}K\right)/\sum_{i\in D} b_i$. Each combination of parameters T, p, and K provides a different nominal capacity, which we report as a percentage. In Table 2, we classify the pairs of (T, p) in 7 groups based on the maximum capacity of 10 vehicles, as (A): 80–90%, (B): 90–100%, (C): 100–110%, (D): 110–120%, (E): 120–130%, (F): 130–140% and (G): over 140%. The maximum ($K = 10$) nominal capacities of each (T, p) pair are presented within each cell in this table.

5.2. Computational performance of the model

To investigate the performance of our heuristic algorithm, we first tested it using small-size instances adopted from the literature. The computational times of each sub-model in Algorithm 1, as well as the reach maximization and cost minimization models for 26 small instances are reported in Table A.1 in the Appendix, to demonstrate the performance of our heuristic algorithm. These instances, which we have adopted from TSPLIB (Reinelt, 1995), include five networks with symmetric distance matrices (`ulysses16, ulysses22, bays29, swiss42, att48`). The distance matrix of each of these instances has been scaled by multiplying by a constant to have the same average as in our case study (25.2 km). The first node of each instance is considered as the central facility, while the potential temporary and mobile facility locations are identical and consist of the first few nodes within the rest of network. That is, for these instances, $|\mathcal{F}| = |\mathcal{P}|$ and equals 1, 2, 3, 5 and 6, respectively for each of the five networks. The risk was ignored and all other parameters were kept the same as our case study.

We use these benchmark instances to investigate the performance of the heuristic approach in terms of both reach maximization and cost minimization. The heuristic solution obtained for each objective is fed into the CPLEX solver as an initial solution, and the improved solution is passed on to the next problem, as the sequence depicted in Fig. 4.

The obtained 'cost' and 'reach' objective values in the illustrated steps are denoted by C_i and R_i, $i \in \{0, \dots, 3\}$ and their corresponding relative changes for $i \in \{1, 2, 3\}$ are calculated as,

$$\Delta C_i\% = \frac{C_i - C_{i-1}}{C_{i-1}} \times 100, \tag{37}$$

$$\Delta R_i\% = \frac{R_i - R_{i-1}}{R_{i-1}} \times 100. \tag{38}$$

Note that as the reach level in the cost minimization model is bounded below by its maximum value (see (36)) and no further improvement happens while minimizing the cost, i.e. $\Delta R_2\%, \Delta R_3\% = 0$. Therefore, these two measures are omitted in Table A.1 of the Appendix. The relative MIP gap of the initial solution fed to CPLEX, and of the final solution found by CPLEX are both provided in this table for the reach maximization and cost minimization models.

The CPLEX solver was restricted to a maximum of 1 h and the realized execution times are presented in seconds. We observe in this table that the solver has improved the objective values with respect to those of the heuristic solutions by a maximum of 7.13% (1.99% on the average) for the reach, and up to 26.59%[1] (6.43% on

[1] $100 \times [(1 + \Delta C_1/100)(1 + \Delta C_2/100)(1 + \Delta C_3/100)/(1 + \Delta C^H/100) - 1]$ in Table A.1

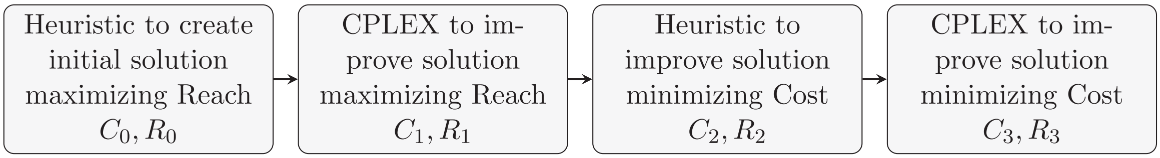


Fig. 4. Benchmark solution construction process for evaluation.

Table 4
Average statistics of Kilis solutions for different capacity configurations .

	Reach maximization							Cost minimization				
	Init. heuristic			CPLEX				Imp. heuristic		CPLEX		
CG	Reach	Cost	time	ΔR(%)	ΔC_1(%)	time	gap(%)	ΔC_2(%)	time	ΔC_3(%)	time	gap(%)
A	84.4	11793.0	85.9	0.00	0.00	661.0	3.36	-2.40	4.3	-0.26	706.4	85.77
B	89.9	13275.0	24.6	0.00	0.02	714.0	0.94	-2.15	4.0	-0.06	1255.0	59.90
C	91.1	14231.9	8.1	0.00	0.01	864.4	0.67	-2.19	4.5	0.00	1474.2	59.46
D	91.6	14647.7	7.5	0.00	0.01	828.7	0.64	-2.51	4.5	0.00	1495.7	58.00
E	92.5	15615.5	8.2	0.00	-0.01	1142.5	0.69	-2.21	5.2	0.00	1677.5	59.56
F	92.7	15661.1	8.3	0.00	0.01	1137.4	0.68	-2.17	5.0	0.00	1749.9	58.46

Table 5
Identified dominant and frontier capacity configurations for Kilis.

CG	#C	#F	#D	NC%	R%	Dominant configurations (T, p, K)
A	112	2	2	86.53	85.38	(7,17,1), (10,12,1)
B	105	9	8	95.18	89.85	(8,17,1), (9,14,1), (10,13,1), (12,11,1), (14,9,1), (14,9,3), (14,9,4), (14,9,5)
C	90	7	6	106.33	93.45	(13,11,4), (14,10,1), (14,10,3), (14,10,4), (14,10,5), (14,10,6)
D	76	13	11	114.61	91.62	(9,17,1), (9,18,1), (10,16,1), (11,15,1), (14,10,7), (14,10,8), (14,11,1), (14,11,2), (14,11,3), (14,11,5), (14,11,6)
E	65	7	6	124.41	91.71	(10,17,1), (14,12,1), (14,12,2), (14,12,3), (14,12,4), (14,12,5)
F	57	15	10	134.87	94.14	(12,16,1), (13,13,10), (13,14,1), (13,14,2),(13,14,3), (14,12,8), (14,12,10),(14,13,3), (14,13,5), (14,13,7)
Total:	505	53	43			

CG: capacity group; #C: number of configurations; #F: number of configurations on frontier line; #D: number of dominant configurations (on frontier but with the least nominal capacity); NC%: average nominal capacity; and #R%: average reach percentages of the dominant configurations.

the average) for the cost objectives. However, CPLEX was not capable of finding any feasible solution within 2 hours for the instances of our case study with 206 nodes, and it failed to improve the obtained heuristic solution. Therefore, these instances have been solved only via the heuristic, without using CPLEX. All computations were implemented on a personal computer equipped with an Intel Core i5-7200U processor running at 2.50 GHz and equipped with 8GB of RAM, using ILOG CPLEX 12.8. We interpret the results below.

For the real case, we have solved a total of 505 instances involving capacity configurations with nominal capacities between 80–140%. The average of factors characterizing the obtained solutions of these instances over each capacity group are presented in Table 3, while the average performance of the algorithm is assessed by comparing it with CPLEX in Table 4. For the sake of brevity only the individual results of the dominant capacity configurations are tabulated in Table A.2 of the Appendix. A dominant capacity configuration is the one whose cost and nominal capacity are the least among those of all others with the same or less level of achieved reach.

5.3. Reach performance of different capacity configurations

The total nominal capacity and the achieved reach by means of temporary facilities, the mobile facilities, and vehicles are depicted in Fig. 5. It can be observed that the temporary facilities have the highest share of the reach across all capacity groups. Vehicles and the mobile facility, perform second and third, respectively. The mobile facility is allocated to densely populated areas that are relatively close to the central facility, while the vehicles are assigned to more remote areas. More importantly, the reach is not increasing in the total nominal capacity. We can see fluctuations in the bar chart of the achieved reach, where the (T, p, K) labels are sorted in ascending order from left to right on the horizontal axis with respect to their corresponding nominal capacities. Obviously, a (T, p, K) combination with lower nominal capacity and higher total coverage percentage is dominant from the viewpoint of coverage (regardless of costs). For instance, (10,12,2) (nominal capacity: 88.18%, achieved reach: 87.53%) dominates (13,9,3) (nominal capacity: 88.27%, achieved reach: 82.75%). Similar dominance can be seen in all capacity groups. Surprisingly, 100% reach has been achieved in only four configurations in which T=14, $p \in \{9, 10, 11, 12\}$ and K=10 in capacity groups C, D, E and F.

5.4. Mobile reach and sensitivity to budget

According to our numerical results, the mobile facility and vehicles contribute to 1.6–14.2% of total reach, but also incur logistics cost. The trade-off between the logistics cost and the percentage of the reached beneficiaries might be of interest to the donors or other stakeholders to see how efficiently the raised funds are spent. For this purpose, we have illustrated the sensitivity of the logistics cost to the reached beneficiaries% for different configurations in Fig. 6.

As discussed before, a nominal higher capacity does not necessarily lead to higher reach. Accordingly, we can observe in this scatter plot that some pairs of (T, p) are dominated by others. A capacity configuration with higher reach and lower cost is preferable and therefore solutions located on the left and the top of the plot are the dominant ones which are connected by a Pareto frontier line in this figure and some statistics corresponding to them are summarized in Table 5. The size of the markers in these graphs are proportional to the number of vehicles in their corresponding configuration. The figures show that when aiming for low costs (the left side of the figure) it is impossible to attain high reach (90% or higher). This is due to the fact that some demand points are not within coverage reach of any of the temporary facilities and require more expensive vehicles, irrespective of the time horizon.

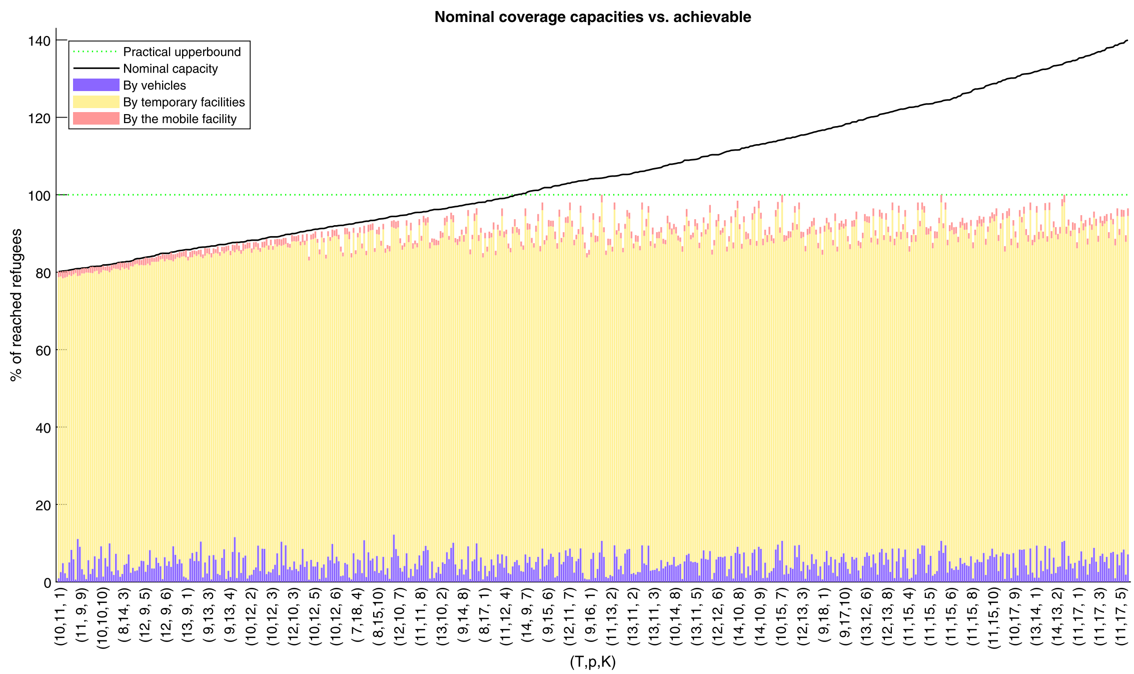


Fig. 5. Achievable refugee population coverage for 505 capacity configurations, (T, p, K), sorted with respect to their nominal capacity in ascending order.

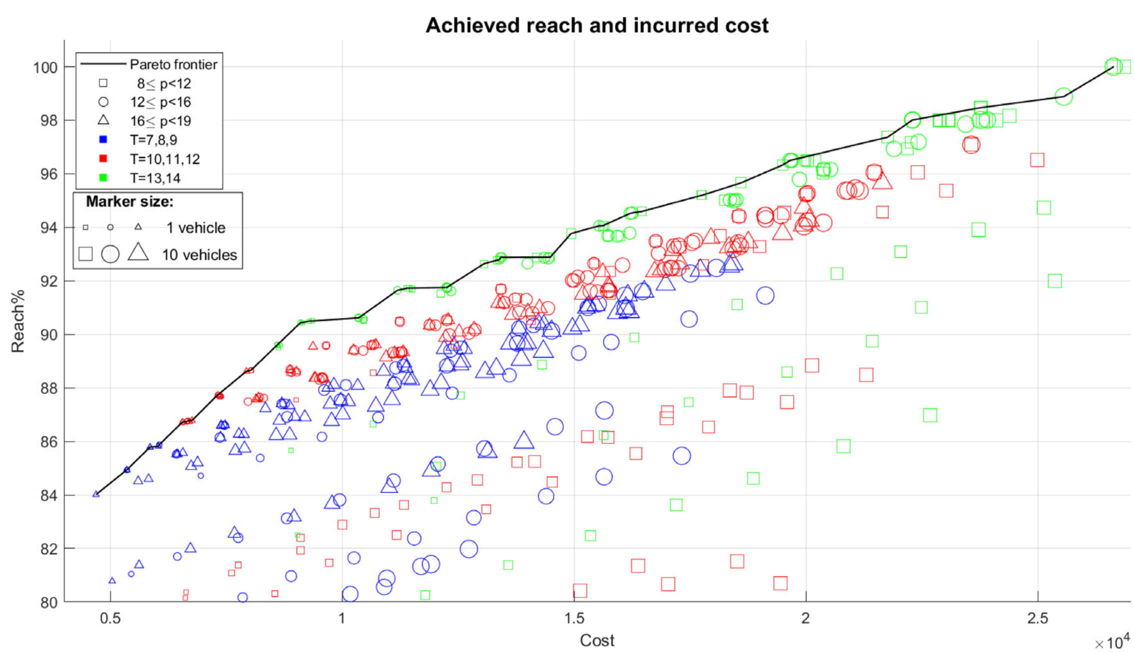


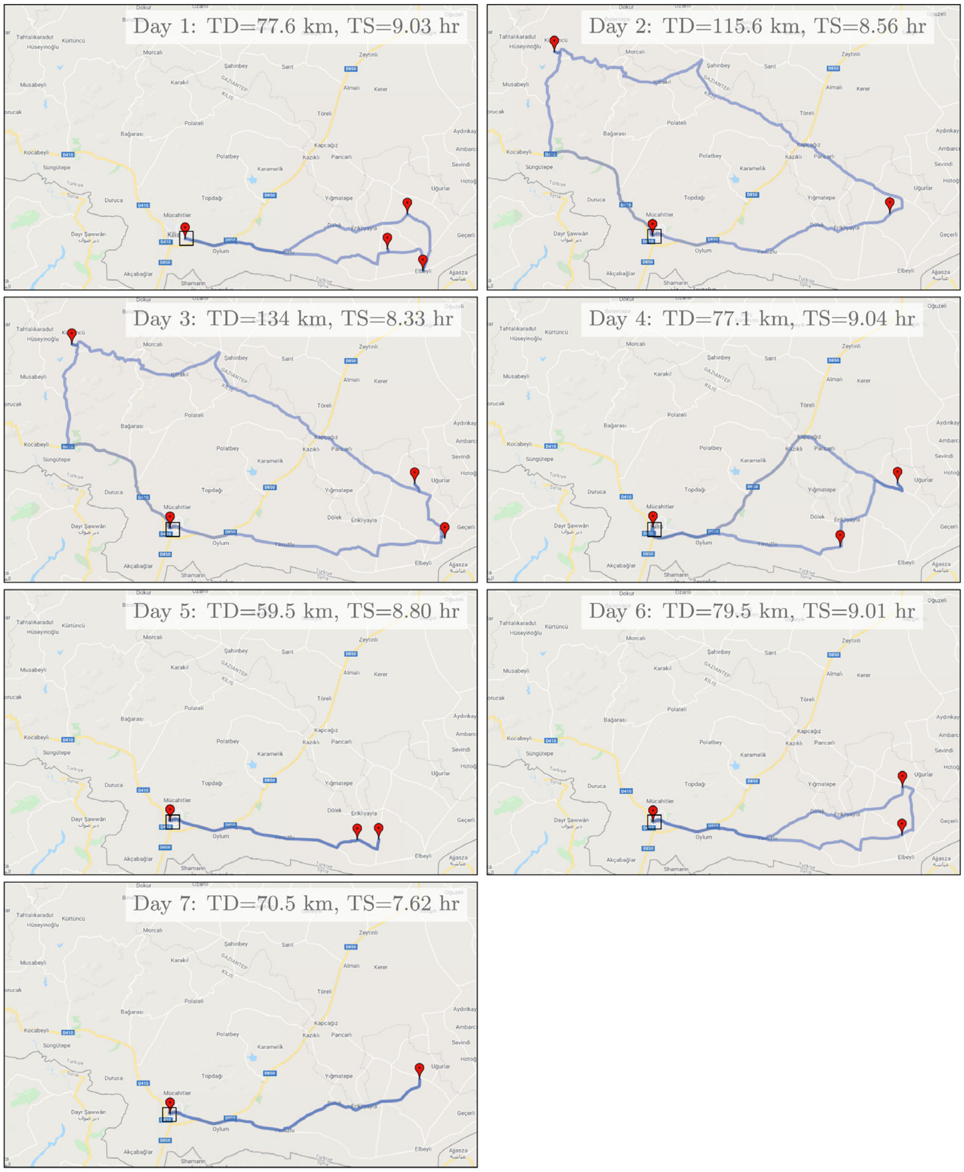
Fig. 6. Cost-Reach trade-off for different nominal capacities: (T, p). Marker sizes are proportional to the number of vehicles..

Higher reach percentages cost more and require longer planning horizons.

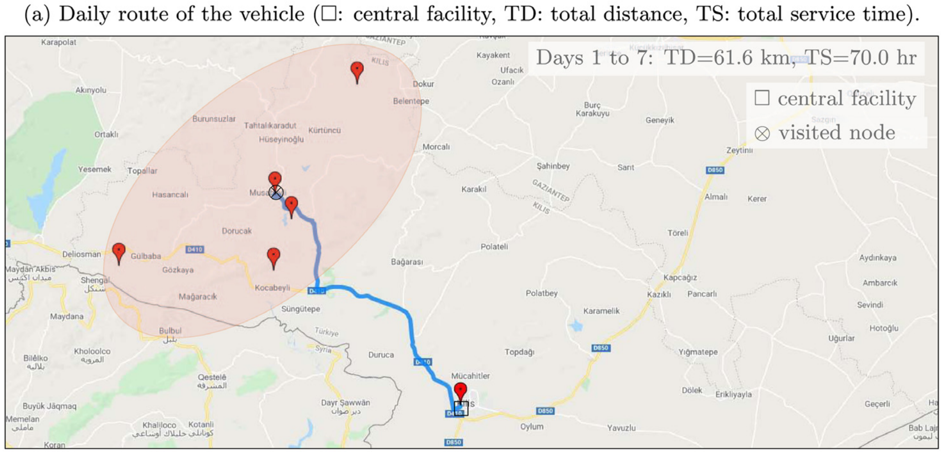
5.5. Visualization of a sample solution

We examine the solution to a sample instance to visualize the resulting network and gain insights. For a planning horizon of $T = 7$ working days, we allow $p = 18$ temporary facilities, and we use K=1 vehicle. This configuration provides a nominal coverage capacity of 90.8% (group B) and an achievable reach of 84.01%. The routes which the vehicle should travel within the 7 days are depicted in Fig. 7-(a) separately. The total distance which should be traveled in these routes is 614 Km. The routes reach 10 demand points covering 483 beneficiaries. As presented in Fig. 7-(b), there is only one location visited by the mobile facility through a 61.6 Km tour, which reaches 4 demand points (illustrated within the highlighted ellipse), with 837 beneficiaries in total. The mobile facility starts its journey from the central facility in Kilis on the first day, arrives in its destination, stays there over the entire planning horizon (T =7 days), and finally returns back to the headquarter on the last day of the planning horizon.

The service points corresponding to the temporary facilities and their covered demand points are depicted in Fig. 8. Part (a) of the figure shows the entire Kilis province with the city center in a circle; part (b) of the figure zooms in on the city center. The location of the temporary facilities are marked with triangles and the other

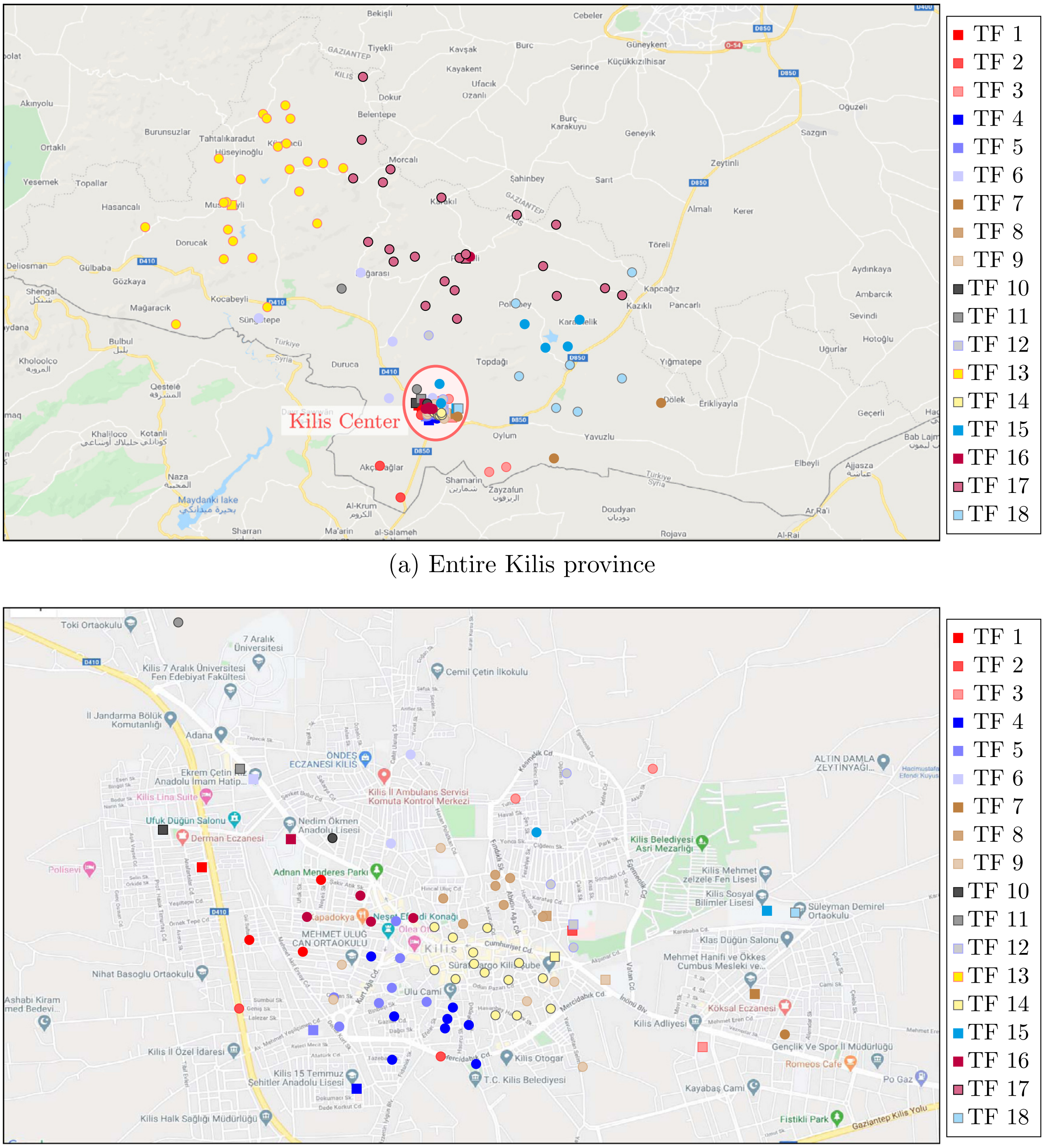


(a) Daily route of the vehicle (☐: central facility, TD: total distance, TS: total service time).



(b) Route of the mobile facility and four other reached nodes within the coverage radius.

Fig. 7. Illustration of the mobile reach for the instance (T=7, p=18, K=1).



(a) Entire Kilis province

(b) Entire Kilis center

Fig. 8. Illustration of the temporary facility coverage for the instances (T=7, p=18, K=1); The demand points are marked with circles having colors of the assigned temporary facilities (TF).

marks denote the demand points. The temporary facilities and the demand points assigned to them are marked with similar colors and their sizes are proportional to the demand.

6. Conclusion

In this paper we investigated the planning of Cash Based Interventions (CBIs) for Syrian refugees in Turkey. We believe we are the first to study the logistics of CBIs quantitatively. For this slow onset disaster, we optimized the design of a service network. We proposed a bi-objective mathematical model and solved two models lexicographically back-to-back. We also designed a solution approach that optimizes decisions on locating temporary facilities for localized distribution, along with routing decisions for a mobile facility covering demand points and vehicles conducting house-to-house distribution. We implemented the model and the proposed solution approach in a real case study of cash distribution in a southern province of Turkey on the border with Syria with a very dense refugee population. We obtained data for this case, resulting in a large input network. A variety of delivery mechanisms based on over 500 capacity configurations, characterized by the length of the planning horizon horizon, as well as the number of allowed temporary facilities and vehicles, were examined and performance levels were compared.

Our numerical results demonstrated that the achievable reach in several capacity configurations is far less than the theoretical (nominal) capacities of these configurations. This implies that capacity will be underutilized in many situations. This may be caused by the fact that it is difficult to reach a dispersed population efficiently within the planning horizon. For a slow onset disaster this may not be as undesirable as it sounds. In fact, when deciding to spend more money on transportation and thus targeting difficult-to-reach people in far-away locations within the planning horizon, less money will be available for the actual financial support of beneficiaries since total budgets are fixed within the planning horizon. We even observed that the achievable reach in some resource configurations with higher surplus of capacity is less than that of the others in the same group of capacity. This is most likely due to inefficiencies in such solutions (the available capacities cannot reach the full population in the specified time).

Our analysis of the trade-off between reach and cost under different capacity configurations confirmed that all the capacity configurations show similar behavior in terms of trend and magnitude in the trade-off of reach vs. cost. As shown in Fig. 6, allowing less cost will decrease the mobile reach over the planning horizon. Of course, this balance may change if transport or facilities are provided for free. Providing cargo space or warehouse space for free is something that is already common for in-kind humanitarian support activities (cf. Richardson, de Leeuw, & Dullaert, 2016), although there is always a setup cost involved (e.g., loading the vehicle).

We furthermore found that certain capacity configurations (T, p, K) are dominant for a certain budget level or for a prescribed reach target level. Our analyses show that there are combinations that outperform the others and in this way form an efficient frontier (i.e., those combinations with the highest reach per cost level; see Fig. 6 in Section 5). The analyses also show that at a given cost level the solutions with the longest planning horizons always lead to higher reach percentages. Therefore, it is advisable to have fewer facilities available for a longer period rather than more facilities for a shorter period.

It was our explicit objective to model a real-life situation using data that is typically available in organizations: capacity information, logistics costs and population sizes are known and real in this case. Only the security risk information may not be readily available but in reality, employees know which areas are riskier than others. If in doubt, risk levels can be assessed using expert input with methods such as AHP (see for example Roh, Pettit, Harris, and Beresford (2015) for an application of AHP to determine facility locations).

This study can be extended in several directions. Our model potentially allows refugees not to be covered presuming that either some refugees at remote locations will need to travel more to reach the facilities, or the unreached part will be served in subsequent and complementary operations as the dynamics of the crisis and refugee population necessitate such arrangements. However, a ranking decision can be incorporated in modeling part to prioritize the most vulnerable refugees first. Another extension of our proposed model may be to incorporate not only CBI but also to include in-kind donations. Although CBI is growing, there may still be a need to support a (part of the) population with goods next to CBI, for example in situations where a part of the necessary commodities is not available on the local market. Trading off in-kind and cash-based interventions is an interesting avenue for future research.

Acknowledgement

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A. Appendix

Table A1
Assessment of the heuristic by feeding its solution to CPLEX for small and medium size instances adopted from TSPLIB.

				Reach Maximization							Cost minimization								
				heuristic		CPLEX					heuristic	CPLEX							
TSPLIB	Pop.*	(N,T,p,K)	CG	Reach	Cost	ΔR_1	ΔC_1	Gap_R^0	Gap_R	time	ΔC_2	ΔC_3	Gap_C^0	Gap_C	time	ΔC^H	TF	MF	V
ulysses16	1122	(16,1,1,2)	A	42.51	263.38	6.92	5.48	9.01	0.00	1.2	-0.81	0.00	57.75	0.00	0.7	4.62	4	0	2
		(16,1,1,4)	B	57.13	529.46	3.12	1.32	5.93	0.15	3600	-2.52	0.00	61.12	0.01	192	-1.24	4	0	3
		(16,1,1,6)	C	71.84	807.73	0.99	1.47	3.82	1.23	3600	-2.25	-0.39	57.96	10.84	3600	-0.90	4	0	5
		(16,1,1,7)	D	77.01	979.90	2.43	-1.06	6.12	1.92	3600	-0.91	-0.92	65.56	15.93	3600	-2.61	4	0	7
		(16,1,1,8)	E	84.85	1120.50	0.63	-0.10	3.99	3.13	3600	-2.18	-0.97	60.38	16.23	3600	-3.01	4	0	8
		(16,1,1,10)	F	93.23	1399.22	1.91	15.81	7.27	5.25	3600	-6.19	-1.56	71.28	21.61	3600	7.14	4	0	9
ulysses22	1133	(22,1,1,3)	A	51.19	410.82	6.72	-3.96	8.85	0.00	3215	-0.85	-0.12	75.66	0.50	3600	-4.89	6	0	4
		(22,1,1,5)	B	63.11	668.27	7.13	3.69	10.56	1.96	3600	-2.18	-0.74	73.69	16.66	3600	0.68	6	0	6
		(22,1,1,6)	C	73.61	810.87	0.84	2.63	4.24	2.66	3600	-1.27	-0.87	68.57	18.88	3600	0.44	6	0	8
		(22,1,1,7)	D	79.26	952.52	1.34	5.25	5.60	3.41	3600	-1.84	-4.91	68.28	18.93	3600	-1.76	6	0	9
		(22,1,1,9)	E	90.64	1275.78	2.04	8.09	6.23	4.10	3600	-1.56	-1.30	65.99	30.96	3600	5.01	6	0	11
		(22,1,1,10)	F	95.41	1451.42	0.83	3.83	4.81	3.94	3600	-2.02	-0.88	71.17	41.95	3600	0.89	6	0	12
bays29	1169	(29,1,1,3)	A	80.50	935.50	0.64	-4.65	1.44	0.00	19.6	-1.58	-0.24	30.91	0.01	38	-4.15	13	3	4
		(29,1,1,5)	B	92.04	1225.19	1.49	-1.18	2.93	0.46	3600	-4.39	-0.66	44.87	2.08	3600	-3.14	13	3	7
		(29,1,1,6)	C	96.15	1394.44	1.33	1.35	4.00	2.63	3600	-5.08	-0.22	55.11	8.22	3600	0.86	12	3	9
		(29,1,1,8)	D	100.00	1582.98	0.00	0.00	0.00	0.00	0.2	-3.77	-7.23	66.45	12.98	3600	-7.23	13	3	9
swiss42	1589	(42,1,2,1)	A	65.76	178.04	2.11	269.82	2.59	0.00	0.4	-3.02	-79.36	39.86	0.00	0.4	-25.98	23	0	2
		(42,1,2,2)	B	69.98	334.71	2.25	148.93	3.54	0.00	509	-0.08	-60.87	72.79	0.00	406	-2.66	23	0	3
		(42,1,2,4)	C	79.30	757.55	1.83	49.55	3.95	1.50	3600	-1.11	-45.80	78.61	29.09	3600	-15.69	23	0	6
		(42,1,2,6)	D	87.54	1074.77	2.52	36.66	5.29	2.31	3600	-1.97	-37.36	76.14	29.97	3600	-12.92	23	0	8
		(42,1,2,8)	E	96.04	1406.12	0.00	0.00	4.13	4.13	3600	-2.77	-14.70	71.16	60.10	3600	-14.70	23	0	11
		(42,1,2,10)	F	100.00	1573.90	0.00	0.00	0.00	0.00	0.4	-2.48	-13.30	68.18	58.78	3600	-13.30	23	0	13
att48	1601	(48,1,2,1)	A	86.38	786.31	0.51	-7.66	1.16	0.00	115	-13.33	0.00	31.52	0.01	43	-14.47	29	3	2
		(48,1,2,2)	B	89.32	932.34	2.73	-9.56	3.32	0.00	3600	-12.35	0.00	52.03	0.01	764	-16.15	30	3	3
		(48,1,2,4)	C	97.63	1274.10	1.41	3.31	2.43	1.01	3600	-8.97	-13.74	65.26	18.84	3600	-15.50	30	4	6
		(48,1,2,6)	D	100.00	1473.14	0.00	0.00	0.00	0.00	0.3	-3.46	-26.59	77.33	42.61	3600	-26.59	31	3	7

'Pop.': Total population; 'CG': Capacity group; 'Gap_R^0' and 'Gap_R': relative MIP gap % of reach maximization model; 'Gap_C^0' and 'Gap_C': relative MIP gap % of cost minimization model; 'ΔC^H': % of cost change by only applying the heuristic to the initial solution; 'TF', 'MF' and 'V': number of nodes served by temporary acilities, mobile facility and veicles, respectively.

* **Demand points population setting** (ϕ_i)**:**`ulysses16`: $\phi_i = \lfloor \frac{1300}{16} \rfloor + (-1)^i (i^2 \bmod 29)$; `ulysses22`: $\phi_i = \lfloor \frac{1290}{22} \rfloor + (-1)^i (i^2 \bmod 19)$; `bays29`: $\phi_i = \lfloor \frac{1400}{29} \rfloor + (-1)^i (i^2 \bmod 23)$; `swiss42`: $\phi_i = \lfloor \frac{1800}{42} \rfloor + (-1)^i (i^2 \bmod 29)$; `att48`: $\phi_i = \lfloor \frac{1300}{48} \rfloor + (-1)^i (i^2 \bmod 27)$

Table A2
The dominant capacity configurations among Kilis solutions.

CG	Cap	(T,p,K)	Reach	Cost	Risk	TF%	MF%	V%	nTF	nMF	nV	nRT	ΔC%	time
A	85.8	(7,17,1)	84.01	4691.1	0.038	82.45	0.99	0.57	139	4	10	7	-1.63	46.6
A	87.2	(10,12,1)	86.74	6652.1	0.043	84.57	1.41	0.76	146	4	12	10	-1.09	74.0
B	98.1	(8,17,1)	84.94	5355.7	0.038	83.16	1.13	0.65	129	4	11	8	-1.3	56.7
B	91.2	(9,14,1)	85.88	6052.8	0.042	83.87	1.27	0.73	139	3	12	9	-1.64	70.0
B	94.3	(10,13,1)	86.78	6665.2	0.038	84.58	1.41	0.78	134	5	12	10	-1.51	69.1
B	96.2	(12,11,1)	88.66	8032.8	0.045	85.99	1.70	0.97	135	12	14	12	-0.94	100.4
B	92.4	(14,9,1)	90.50	9355.0	0.048	87.41	1.98	1.12	146	5	15	14	-1.19	132.9
B	95.1	(14,9,3)	92.77	13338.8	0.049	87.41	1.98	3.38	138	8	25	41	-2.18	776.2
B	96.4	(14,9,4)	94.06	15614.7	0.049	87.41	1.98	4.67	129	5	29	56	-2.38	1650.7
B	97.7	(14,9,5)	95.19	17753.4	0.049	87.41	1.98	5.81	139	5	32	69	-2.01	2609.6
C	107.9	(13,11,4)	92.89	14484.4	0.049	86.70	1.84	4.35	134	5	26	52	-1.82	1308.6
C	102.3	(14,10,1)	90.50	9288.2	0.047	87.41	1.97	1.12	150	4	15	14	-1.28	120.6
C	105.0	(14,10,3)	92.64	13055.2	0.049	87.41	1.98	3.25	142	4	23	39	-1.42	877.8
C	106.3	(14,10,4)	93.77	14933.7	0.049	87.41	1.98	4.38	141	6	26	52	-1.87	1368.5
C	107.6	(14,10,5)	94.59	16457.5	0.049	87.41	1.98	5.21	137	6	28	62	-1.79	2527.0
C	108.9	(14,10,6)	96.32	19491.0	0.050	87.41	1.97	6.95	150	4	30	82	-2.36	4393.2
D	110.3	(9,17,1)	85.82	6036.6	0.044	83.87	1.27	0.68	126	7	11	9	-1.79	61.7
D	116.7	(9,18,1)	85.79	5855.7	0.038	83.87	1.27	0.65	139	4	11	8	-1.17	68.9
D	115.5	(10,16,1)	86.78	6760.2	0.042	84.58	1.41	0.79	137	3	13	10	-1.84	66.7
D	119.3	(11,15,1)	87.74	7316.7	0.043	85.28	1.56	0.90	146	5	13	11	-1.05	89.9
D	110.2	(14,10,7)	97.37	21754.8	0.050	87.41	1.98	7.98	139	5	31	96	-1.65	5850.6
D	111.6	(14,10,8)	98.47	23769.7	0.050	87.41	1.97	9.10	150	4	32	109	-2.84	7238.2
D	112.2	(14,11,1)	90.44	9153.8	0.043	87.41	1.98	1.06	147	5	14	13	-0.85	135.2
D	113.5	(14,11,2)	91.72	11398.1	0.049	87.41	1.98	2.34	147	5	20	28	-1.82	365.8
D	114.9	(14,11,3)	92.79	13386.6	0.049	87.41	1.98	3.40	147	5	24	41	-2.12	909.3
D	117.5	(14,11,5)	95.19	17742.2	0.049	87.41	1.98	5.81	147	5	31	69	-3.38	2519.9
D	118.8	(14,11,6)	95.66	18595.0	0.049	87.41	1.98	6.27	147	5	32	75	-2.86	4362.9
E	122.6	(10,17,1)	86.72	6555.0	0.042	84.58	1.41	0.73	139	6	12	9	-1.1	73.8
E	122.1	(14,12,1)	90.44	9099.9	0.043	87.41	1.96	1.07	152	4	14	13	-0.86	147.2
E	123.5	(14,12,2)	91.65	11189.2	0.049	87.41	1.96	2.28	152	4	19	27	-1.12	408.2
E	124.8	(14,12,3)	92.88	13409.7	0.049	87.40	1.98	3.50	142	7	23	42	-1.68	823.1
E	126.1	(14,12,4)	94.06	15538.3	0.049	87.41	1.96	4.69	152	4	26	56	-1.43	1541.1
E	127.4	(14,12,5)	94.52	16207.9	0.049	87.41	1.96	5.15	152	4	27	61	-1.77	5247.7
F	138.6	(12,16,1)	88.62	7933.1	0.043	85.99	1.70	0.93	149	3	13	12	-0.95	95.1
F	133.6	(13,13,10)	98.88	25554.4	0.050	86.70	1.84	10.34	144	6	36	123	-2.34	5766.7
F	131.8	(13,14,1)	89.61	8599.9	0.043	86.70	1.84	1.07	146	6	14	13	-1.01	107.8
F	133.0	(13,14,2)	90.62	10350.9	0.049	86.70	1.84	2.08	146	6	18	25	-1.3	356.3
F	134.3	(13,14,3)	91.75	12249.9	0.049	86.70	1.84	3.21	146	6	22	38	-3.22	701.0
F	131.4	(14,12,8)	98.01	22293.9	0.049	87.41	1.96	8.64	152	4	30	101	-2.17	6835.3
F	134.0	(14,12,10)	100.00	26631.7	0.049	87.41	1.96	10.63	152	4	31	127	-3.29	1425.7
F	134.7	(14,13,3)	92.88	13440.0	0.049	87.41	1.98	3.50	142	6	23	42	-1.6	892.9
F	137.3	(14,13,5)	94.54	16249.7	0.049	87.41	1.98	5.15	140	10	27	61	-1.52	2725.3
F	140.0	(14,13,7)	96.50	19652.7	0.049	87.41	1.98	7.11	137	6	29	84	-1.53	5344.6

'CG': capacity group; 'Cap':nominal capacity (in %); 'T': planning horizon (days); 'p': number of temporary facilities; 'K': number of vehicles; 'Reach': % of registered refugees; 'TF%': contribution of fixed facilities; 'MF%': contribution of the mobile facility; 'V%': contribution of vehicles; 'nTF': number of nodes served by temporary facilities; 'nMF': number of nodes served by mobile facility; 'nV': number of nodes visited and served by vehicles; 'nRT': number of routes;'Δ*C*%': cost change of reach maximization model; 'time': total computational time (s)

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