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Modeling mobile health service delivery to Syrian migrant farm workers using call record data

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ABSTRACT

A significant number of Syrian refugees under temporary protection in Turkey work in agriculture seasonally in various rural areas during several months a year. These migrant farm workers and their families are deprived of access to the regular health care system and preventive services due to their remote locations. The government supports the delivery of different types of mobile health care services, such as vaccination for children, reproductive health and screening services. While planning the mobile health care service delivery, it is critical to know where the refugees will work during what time frame; hence the demand for the services. By analyzing the call record data of a major mobile network operator in Turkey, we quantify the increase in the volume of calls made by Syrian refugees in various agricultural areas during the harvesting season of local crops. This information helps us to forecast spatial and temporal distribution of demand for mobile health care services at a fine granularity. Taking demand over multiple periods as input into a mathematical programming model, we optimize the routing of mobile clinics that visit locations close to where refugees are concentrated over the given planning horizon. We consider three hierarchical objectives. Given the availability of a number of mobile clinics at community health centers in the districts, the first objective aims to maximize the percentage of refugees that can benefit from each service type within pre-defined close distances. The second objective minimizes the number of clinics needed while covering the maximum percentage of refugees. The third objective minimizes the total travel distance of the clinics, while keeping the maximum coverage level using a minimum number of clinics to achieve this level. We quantify the benefits of centralized planning (by the province directorate) over decentralized planning (by each district separately). We also show the trade-off between the required number of clinics and coverage of potential patients.

1. Introduction

In this paper, we focus on health service delivery to Syrian Seasonal Migrant Farm Workers (SMFWs) in Turkey by means of mobile clinics. We aim to increase the reach of these services by identifying where SMFWs are located throughout a rural area during a harvesting season and bringing the services closer to the most number of beneficiaries while utilizing the available resources more efficiently. With these goals in mind, we first analyze the call record data of refugees, obtained from a major telecommunications company, to identify the number of Syrian SMFWs and their spatial distribution. Having estimated the number of beneficiaries at various locations, we develop mathematical programming models to optimize the visit schedule of the clinics over a planning horizon covering the harvesting season, under the consideration of several service effectiveness and efficiency objectives hierarchically. We next present background information on the case that drives our study and then give an overview of our optimization approach.

Since the onset of the Syrian conflict in March 2011, Turkey has pursued a generous open-door policy towards those Syrians fleeing conflict over the last nine years and currently hosts more than 3.6 million Syrian nationals. Syrian nationals in Turkey are not granted with refugee status; however, their access to basic services are regulated through the temporary protection regime that was adopted in March

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2014. Under current regulations, Syrians under temporary protection status in Turkey are granted with access to free health care services only in those provinces that they are registered at except for emergency situations. However, the mentioned conditionality on free health care services constitutes a major obstacle in accessing health care services, especially for those Syrians working in the agricultural sector since they often move out of the provinces that they are registered at in pursuit of seasonal work opportunities in some other provinces within Turkey. Therefore, it becomes crucial to provide preventive health care services to Syrian agricultural workers not only because they often have restricted access to free health care services, but also because they are more likely to be exposed to occupational and environmental hazards.

Earlier studies document that Turkey, in comparison to other host countries in the region, hosts relatively a higher number of Syrian farmers who have migrated from rural areas [1]. While agricultural work experience of Syrians accounts for their frequent involvement in agricultural sector in Turkey, a report by Development Workshop on the migrant workers in seasonal agriculture in Adana also indicates that the inability to find work in their primary occupations is also a crucial reason for Syrians' participation to the agricultural sector [2]. Previous studies hint that Syrians working in seasonal agricultural jobs in Turkey migrate between provinces to work in the harvesting of agricultural products such as hazelnut, apple, and cotton [3]. The analysis of the call record data of Syrians living in Turkey between January 2017 and December 2017 also indicates that nearly 20% of the Syrians has migrated between provinces and the seasonal agricultural work has been an important driver of the inter-provincial mobility of Syrians under temporary protection [4].

Working in seasonal jobs, especially in agriculture, indicates not only the problems of exploitation, precarity, chronic poverty, insecurity, but also problems in accessing health care services [5]. Under current conditions, many Syrians working in seasonal agriculture are faced with unhealthy and unsafe conditions with little access to education, health, and other social services [1].

Farm workers are exposed to various negative conditions during work including adverse living environment for especially migrant farm workers. International Labour Organization (ILO) considers agricultural work as one of the three most hazardous occupations in the world and highlights the diversity of government capacity to provide protective services for workers in this sector. Working with machinery, means and quality of transportation, injuries due to accidents and animals, ergonomic conditions, physical conditions including noise, vibration and dust, chemical hazards such as pesticides and weather conditions are among the factors that contribute to the worsening of farm workers' health [6]. These factors are exacerbated for especially seasonal migrant farm workers, who are deprived of decent housing, clean water and sanitation, health care and educational services in addition to above mentioned hazards. Also, discrimination, job insecurity, lack of social insurance, child labor, lack of access to quality food and precarious work are among social hazards of working as a SMFW. Health consequences of these conditions for SMFWs in Turkey are that infant mortality is four times and maternal mortality is 10 times higher than the Turkish national average [7,8]. Furthermore, during infectious disease emergencies such as pandemics, SMFWs are considered as an essential workforce in agriculture, who are exempt from lock-down measures or travel restrictions [9]. Preventive measures for COVID-19 are isolation and quarantine for the sick and social distancing, hand washing and working from home [10]. However, SMFWs lack the conditions to fulfill these measures because of their unfavourable working, living and transportation conditions. Along with their refugee status, SMFWs become a highly vulnerable group during pandemics that require further services.

The capacity of Turkish governmental agencies in meeting the needs of agricultural workers is limited albeit the available legislation already in use. A Prime Minister Circular aims to meet the needs of SMFWs with the coordinated efforts of different governmental agencies at the local level [11]. One of the interventions named in this circular is mobile health services where necessary to cover basic needs such as immunization, reproductive and child health needs, health education, and water sanitation. It has been well documented that mobile services significantly contribute to improve the health of SMFWs and restore social justice [12,13].

Providing basic health needs to SMFWs by means of mobile health clinics is a practical and economic solution approach. The goal is to reach to the highest number of SMFWs that are dispersed in an agricultural region. However, the locations where mobile clinics will stop and service SMFWs need to be chosen carefully to provide the most benefit. The candidate stop locations can be villages close to SMFW concentrations, which need to be identified first. To address this issue, the current study utilizes mobile call data records of Syrians under temporary protection in Turkey provided by a major mobile service provider under the *Data for Refugees: The D4R Challenge on Mobility of Syrian Refugees in Turkey* ([14]) and examines temporal and spatial dimensions of seasonal agricultural work to estimate the needs for different types of services to be provided by mobile health care teams. In current practice, the planning of mobile services is not optimized in a systematic and centralized way, leaving room for more effective allocation of the clinics to the most beneficial regions. In our study, we take into account criteria determined by health care administrators, and optimize the plans by defining the objectives accordingly. Planning encompasses: 1) selecting the service locations to provide each type of service within reachable distances to the most number of people, 2) scheduling visits to the selected service points over multiple days, by ensuring the required service frequency for each service type, during the harvesting season, 3) finding out with what number of clinics originating from which community health centers the maximum coverage level of people can be achieved, and 4) finding the routes of the determined number of mobile clinics that minimize the total travel distance. This is achieved by means of running three mathematical models with three prioritized objectives (maximize coverage, minimize the number of clinics, and minimize the total travel distance) back to back according to the priority of the three objectives.

According to Levesque [15] there are five dimensions for accessibility of health services: approachability, acceptability, availability, affordability, and appropriateness. Mobile health services are outreach activities to increase the approachability of services needed by Syrian SMFWs. Also, they help distribute the health care resources fairly to ensure availability of services in rural areas. As these services are designed for Syrian SMFWs, they are provided free of charge in a culturally appropriate way, as well as in Arabic. Lastly, the scope of the services include the most needed services to be provided appropriated to SMFWs' duration of stay at one location. Therefore, our modeling approach aims to achieve maximum coverage as the first objective.

In the next section, we compare our work with the related literature according to the structure of our optimization problem. In Section 3, we provide the problem definition and the main mathematical formulation for it. Section 4 presents an application of our approach to a case study for two provinces of Turkey, namely Malatya and Rize, where Syrian agricultural workers are accommodated intensively. The paper is concluded with an overview of the study and insights obtained through the case analysis and future work suggestions.

2. Literature review

Our problem, which involves multi-depot selective routing with tour distance limits also imposes visit frequencies for multiple service types over a planning horizon. The problem requires that the highest possible portion of the total demand for each service type is covered, i.e. at least one clinic stops and gives service within a specified short distance from the covered demand points. As such, this problem has not been studied before to the best of our knowledge. Therefore, in this section we compare problems that have similarity to ours with respect to different aspects and review the related studies briefly.

In our problem, while the facilities, i.e. the clinics, are mobile, the demand, that is, the SMFWs stay at the same location throughout the planning horizon. Several studies focus on the movement of mobile facilities along with customer movements to receive service in a single period. [16] presented a continuous time formulation to model the maximum covering mobile facility routing problem for both single and multiple facilities. Later on, [17] studied the mobile facility location problem with one-time relocation decisions, where the objective is to minimize the weighted travel costs of both the facilities and the customers. They provided mathematical formulations and developed local search heuristics for the problem. Recently, [18] extended the problem to the case with multiple types of capacitated facilities and presented a branch-and-price algorithm and two heuristics. We stress here that in these studies a multi-period planning horizon is not taken into consideration. On the other hand, [19] studied the mobile facility routing and scheduling problem, in which the aim is to decide the routes and the schedule simultaneously for a fleet of mobile facilities over a multi-period planning horizon. The goal is to assign customer demands to the facilities and to determine the amount of demand to be outsourced in order to minimize the total expected cost. The authors formulate a two-stage stochastic programming model and develop an algorithm based on the multi-cut version of the L-shaped method, in which several lower bound inequalities are generated. [20]also considered demand uncertainty, but proposed a robust optimization model for the mobile facility fleet sizing and routing problem. They developed a two-level cutting-plane-based method for the two-stage problem that combines heuristic and exact methods. While these two studies address mobile facility location over a multi-period planning horizon, they differ from our study in that in those studies the demand is stochastic and multiple types of services do not exist.

In an application-oriented study, [21] address location and routing decisions for mobile health care clinics over a multi-period planning horizon for a for-profit company. The objective is to maximize the full and partial coverage of potential patients with respect to their work and residence distances from the clinics' visit points that are selected from points of interest. Their problem differs from our problem not only with respect to the objectives, but also the fact that multiple service types and their visit frequency requirements are not considered in that study, while we do so. [21] derived their model parameters from an analysis of credit card expenditure data (in contrast, our data sets come from mobile call records). The locations of potential customers and their demand, in addition to potential service locations, were estimated from data analyses. In the current study, we consider a non-profit service provided by the government and define our objectives correspondingly. That is, our goal is to maximize the number of refugees covered with a minimum number of mobile clinics and to position the clinics at community health centers at the districts for tactical planning, as well as generating a schedule and a routing plan over a couple of months that minimize the total travel distance, at the operational level.

The mobile facility location and routing problem that we study has similarity to the so-called Dynamic Facility Location Problem (DFLP) and the class of Multi-period Facility Location Problems (MFLPs) in that the facilities are relocated over time. The reader can refer to Ref. [22] for a detailed overview of the DFLP and to Ref. [23] for a discussion on MFLPs. While these problems and our problem both involve making location decisions of multiple facilities over time, our problem explicitly accounts for the traveling distance of the mobile clinics, hence the routing aspect, while the DFLP and MFLP do not. We also note that in our problem potential stop locations are selectively visited by the mobile clinics and distance limits exist between the depot and the visit locations.

The Team Orienteering Problem (TOP) (see Refs. [24,25] for reviews) is somewhat related to our problem since in both there is the need to decide on which locations to visit. In the TOP, a team of players collects rewards from different locations to maximize the total collected reward within a given time limit. Correspondingly, in our problem, rewards correspond to the number of people at the demand points, but the problem involves finding routes over a multi-period planning horizon. Although the TOP has been extensively studied together with several variants (such as having time windows [26] and a clustered structure [27]), we have found no studies on the multi-period TOP.

In our problem, where multiple vehicles (clinics) departing from their depots visit the selected stop points, a demand point is covered for a service type when it is located within an acceptable distance from at least one clinic's stop point where it can serve its demand. The coverage aspect, together with routing, has been addressed in covering tour problems with multiple vehicles (MVCTPs) in the literature. In the MVCTP, the goal is to construct minimum length routes to cover all of the demand points. However, in our problem, it is allowed not to cover each one of the demand points due to time and distance limitations; rather, we maximize the covered population, and cost minimization comes next. Furthermore, our problem has a multi-period planning horizon, where the visits are scheduled to each period (day) on a visit frequency basis. [28] studied the MVCTP, motivated by several practical applications, including the design of the routes for mobile health care delivery teams. The authors proposed a mathematical formulation and three heuristic algorithms for the problem that they introduced. Later on, both [29,30] developed a branch-and-price algorithm for this problem. [31], in addition, constrained the length of the tours and the number of vehicles. They developed a branch-and-cut algorithm using a mixed integer programming formulation based on a two-commodity flow model, as well as an evolutionary local search metaheuristic. A hybrid metaheuristic combining greedy adaptive randomized search procedure (GRASP), iterated local search and simulated annealing was proposed by Ref. [32]. [33] considered three variants of the MVCTP, where a customer must be covered several times. They developed a branch-and-cut method for a special case and a genetic algorithm that outperforms the previous ones. Recently, [34] extended the problem with probabilistic coverage. They developed a branch-and-cut algorithm, together with a local search heuristic based on the variable neighborhood search structure.

Bi-objective versions of the MVCTP have also been studied within the last decade. In these studies while the first objective is to minimize total routing cost, the second objectives differ. [35] minimize the expected uncovered demand, where demands are uncertain. On the other hand, both [36,37] minimize the maximum coverage distance. In our problem setting maximizing the total demand covered withing the coverage distance is the first objective.

Our problem considers clinics originating from a set of depots and in this aspect, it has similarity with the Multi-depot VRP (see Ref. [38] for a review and the articles discussed in Ref. [39] for more recent work). However, in our problem, we consider routing decisions over several days. In this aspect, a related study given by Ref. [40] focuses on a multi-period multi-depot VRP and proposes an Adaptive Large Neighborhood Search (ALNS) based matheuristic algorithm for its solution. Another routing problem that spans multiple-periods and presents similarities to our problem is the well-studied Periodic Vehicle Routing Problem (PVRP). In PVRP, each customer has an associated set of allowable visit schedules, and the objective of the problem is to design a set of minimum cost routes that give service to all the customers respecting their visit requirements [41]. We note that [42] review the PVRP studies. On the other hand, [43] studied the flexible PVRP, in which customers are visited according to a certain periodicity, as in our case. Therein the quantity to deliver to each customer at each visit is a decision variable. An iterative two-phase matheuristic is developed to solve the problem. Our problem also obeys the flexible periodic visit requirement, however, different frequencies exist for different types of services. In addition, we allow visits at most on a few days of the work week so that the health workers can attend their regular work as well. Furthermore, we minimize the number of mobile clinics as our secondary objective and decide on the allocation of the mobile clinics to the depots at the same time. On another note , [44] studied a PVRP where visits may only occur in one of a given number of allowable visit patterns with vehicles originating from a set of depots. In addition, they consider a maximum route duration constraint and vehicle capacities. Moreover, the cost of each vehicle route is computed through a system of fees depending on the distance that is traveled. This type of VRP is typically called the multi-depot periodic vehicle routing problem (MDPVRP). [45] studied the MDPVRP, together with fleet management, in which they decide on the number of vehicles to rent, the assignment of vehicles to plants, and the routes between plants and distribution centers, while minimizing the total transportation cost. The problem, motivated by a real situation faced by a brewing company in Mexico, also sets due dates and time windows. The authors proposed a mixed integer program and a reactive GRASP to solve this complex problem. [46] proposed a multi-thread cooperative search method for multi-attribute combinatorial optimization problems and tested its performance on MDPVRP instances.

Here we stress again that while some characteristics of the above discussed problems co-exist in our problem, since our problem is defined to satisfy the requirements of the real planning problem, it is unique in its structure. This can be seen in Table 1, where we compare key characteristics of the related problems. Nevertheless, the model that we formulate can also be used in other mobile facility location and routing problems where multiple services are provided with differing frequencies over a planning horizon, for instance in provision of educational services.

3. Problem definition and the mathematical model

The problem is defined over a planning horizon, composed of consecutive days, which corresponds to the harvesting season. There are multiple types of services (such as vaccination, screening, gynecology, health education, etc.) to be delivered to different patient groups with different frequencies. The frequency of a service type is defined in terms of the maximum number of days allowed between two consecutive visits. A fleet of mobile clinics, where each clinic is capable of delivering a specified set of service types is available. Thus, a clinic may provide more than one service type on a day. A set of locations with SMFW concentration having the need for at least one type of service, called demand points, is given together with a set of potential service locations in the vicinity of the demand points. Each day, if a clinic is employed, it should start from its depot (the hosting community health center), visit one service location, and return back to its depot at the end of the day. A patient is likely to participate in a service if a mobile clinic gets close enough to where he/she is positioned. We assume that having a clinic visit a location provides full coverage of the demand up to a certain distance from it, where the coverage distance differs via service types. Covering the demand of a point for a service type requires that at least a clinic providing that type of service stops at a point within the required distance at least once in a specified number of days. A demand point can get the service from any clinic providing that service type that is close enough as specified by the coverage limit and the same clinic does not need to follow the service throughout the horizon. We do not consider any service capacity limitation since it is assumed that the clinic stops at the demand point for a sufficiently long time and the service capacity of a clinic on each day is assumed to be determined after the service schedule decisions. The goal is to maximize the number of covered people over all services with the minimum number of mobile clinics. The problem is to decide on which clinics located at which depots are needed, which locations to stop at each day and the routes of the clinics over the planning horizon. Next, we present the notation and the formulation of our binary integer programming (BIP) model to solve this problem.

Sets:

S	set of service types
K	set of mobile clinics
K_s	set of mobile clinics that can provide type s service for $s \in S$, where $K_s \subseteq K$
T	set of days in the planning horizon
W	set of weeks in the planning horizon, where $\|W\| = \|T\|/4$
J	set of demand points
L	set of potential visit locations
D	set of depot locations of the clinics

Parameters:

d_{ij}	distance between potential visit location i and depot location or demand point j, where $i \in L$ and $j \in (D \cup J)$
l_{js}	coverage distance limit of demand point j for service type s, $j \in J, s \in S$
w_{js}	total demand of type s at demand point j, $j \in J$, $s \in S$
e_{js}	maximum number of days between consecutive visits allowed for demand point j and service type s, $j \in J$, $s \in S$
a_{ijs}	1, if demand point j can be served by a clinic providing service type s at location i, i.e. $d_{ij} \le l_{js}$; 0, otherwise, $i \in L, j \in J, s \in S$
o_k	depot location of clinic k, $k \in K$, $o_k \in D$
v_k	maximum number of days that clinic k can work in a week, $k \in K$
t_w	first day of week w, $w \in W$, $t_w \in T$
c	

(continued on next page)

Table 1
Comparison of related problems.

Problem	Demand	Multi-period	Selective Routing	Multi-depot	Multi-service	Visit frequency	Objective
Dynamic Facility Location [22,23]	Dynamic	YES	NO	NO	NO	NO	Customer-facility distances
Mobile Facility Location [16–18]	Moves	NO	NO	NO	NO	NO	Travel costs
Multi-vehicle Covering Tour [28–31]	Fixed	NO	NO	NO	NO	NO	Travel costs
Multi-depot VRP [9,38]	Fixed	NO	NO	YES	NO	NO	Travel cost
Multi-depot Multi-period VRP [40]	Fixed	YES	NO	YES	NO	NO	Travel cost
Periodic VRP [41,42,45]	Fixed	YES	NO	YES/NO	NO	YES	Travel cost
Our Problem	Fixed	YES	YES	YES	YES	YES	Coverage No. of vehicles Travel cost

(*continued*)

	maximum traveling distance allowed between the depot location and a potential visit point
α_s	minimum service level for service type s, $s \in S$

Decision Variables:

X_{ikt}	1, if location i is visited by a clinic k on day t; 0, otherwise, $i \in L$, $k \in K$, $t \in T$
Z_{js}	1, if demand point j's demand of type s is covered; 0, otherwise, $j \in J$, $s \in S$
F_{jst}	1, if demand point j is covered by a clinic that can provide type s service on day t; 0, otherwise, $j \in J$, $s \in S$, $t \in T$
V_{kt}	1, if clinic k is employed on day t; 0, otherwise, $k \in K$, $t \in T$
U_k	1, if clinic k is employed at least once over the planning horizon; 0, otherwise, $k \in K$

Constraints:

$$d_{i,o_k} X_{ikt} \le c, \forall i \in L, k \in K, t \in T, \tag{1}$$

$$\sum_{i \in L} X_{ikt} \le V_{kt}, \forall t \in T, k \in K, \tag{2}$$

$$a_{ijs} X_{ikt} \le F_{jst}, \forall i \in L, j \in J, s \in S, k \in K_s, t \in T, \tag{3}$$

$$F_{jst} \le \sum_{k \in K_s} \sum_{i \in L} a_{ijs} X_{ikt}, \forall j \in J, s \in S, t \in T, \tag{4}$$

$$\sum_{t'=t}^{t+e_{js}-1} F_{jst'} \ge Z_{js}, \forall j \in J, s \in S, t \in T : (t + e_{js} - 1) \in T, \tag{5}$$

$$\cancel{\sum_{j \in J} w_{js} Z_{js} \ge \alpha_s \sum_{j \in J} w_{js}, \forall s \in S,} \tag{6}$$

$$\sum_{t'=t_w}^{t_w+6} V_{kt'} \le v_k, \forall k \in K, w \in W, \tag{7}$$

$$V_{kt} \le U_k, \forall k \in K, T \in T, \tag{8}$$

$$X_{ikt}, V_{kt}, U_k \in \{0,1\}, \forall i \in L, k \in K, t \in T, \tag{9}$$

$$F_{jst}, Z_{js} \in \{0,1\}, \forall j \in J, s \in S, t \in T. \tag{10}$$

Constraints (1) guarantee that the traveling distance between the depot of a clinic and a visited location is not more than the maximum distance allowed. Constraints (2) guarantee that if employed, a clinic can visit at most one location on a day. Constraints (3–4) guarantee that a demand point is covered for a service type on a day if a location in its coverage distance is visited by a clinic providing that service type on that day. Constraints (5) ensure that demand of a point for a service type is covered only if the demand point is served periodically according to the specified frequency of the corresponding service type. Constraints (6) guarantee that the specified service level is met for each service type. As the clinics may not be used during the whole work week due to the regular duties of the personnel at the health centers, constraints (7) ensure that a clinic k can provide service in at most v_k days of the week. Constraints (8) identify which clinics are used during the planning horizon. Constraints (9-10) define the binary variables.

Three models address the three hierarchical objectives of the problem. Given the availability of a number of mobile clinics at each depot, the first model, model **M1**, aims to maximize the total demand covered over all service types using the objective function in (11) subject to all of the constraints given above except the service level constraints (6) as follows:

$$\begin{aligned} &\mathbf{M1}: \quad \text{Max} \sum_{j \in J} \sum_{s \in S} w_{js} Z_{js} \\ &\text{s.t.Constraints} \quad (1)-(5), \quad (7)-(10) \end{aligned} \tag{11}$$

The second model, model **M2**, minimizes the number of clinics needed through the objective function in (12) while covering the maximum covered demand of each type found by the first model separately through the service level constraints (6) and all other constraints as follows:

$$\begin{aligned} &\mathbf{M2}: \text{Min} \sum_{k \in K} U_k \\ &\text{s.t.Constraints } (1)-(10) \end{aligned} \tag{12}$$

The third model, model **M3**, minimizes the total travel distance using the objective function in (13) while covering the maximum covered demand of each type found by the first model separately through the service level constraints (6), as well as using the number of clinics at the depots specified by the solution of model **M2**, namely, U_k^* in addition to all other constraints as follows:

$$\begin{aligned} &\mathbf{M3}: \text{Min} \sum_{t \in T} \sum_{i \in L} \sum_{k \in K} (d_{o_k,i} + d_{i,o_k}) X_{ikt} \\ &\text{s.t.Constraints } (1)-(10) \end{aligned} \tag{13}$$

$$U_k = U_k^*, \quad \forall k \in K \tag{14}$$

We observed the computational tractability of these models on real datasets with differing problem sizes in our computational study presented in the next section.

4. Case analysis

We used the proposed mathematical models to plan the mobile health care service delivery to Syrian refugees under temporary protection in Turkey that work in agriculture seasonally in various rural areas during several months a year. In the presented case, we performed separate analyses for two provinces of Turkey, namely Malatya and Rize, where Syrian agricultural workers concentrate intensively and different geographical characteristics impact the spatial demand distribution. In Section 4.1, we describe how we generated the problem data for each province and in Sections 4.2 and 4.3, we present the results of the analysis for Malatya and Rize, respectively.

The mathematical models **M1**, **M2** and **M3** are solved using CPLEX 12.6.2, with an optimality gap limit of 0.1%. The optimal solution of the first model, **M1**, is used as a warm start for the second model, **M2**, and similarly, the solution of the second model is used as a warm start for the third model, **M3**. The number of clinics used, the total coverage percentage and the total run time for the optimal solutions of the three models are provided in the result tables. All computational experiments were performed on a computer with Intel(R) Core(TM) i9-7920X processor running at 2.90 Gigahertz and 64 Gigabytes of memory.

4.1. Data

The input data for the analysis is comprised of service types to be provided; the set of demand points and the demand amount for each service type at each demand point; the set of clinics, the service types provided by each one and their depot locations; and the potential visit locations and covered demand points by each potential location. The government supports the delivery of three different types of mobile healthcare services; namely, vaccination for children, reproductive health and screening services, and health education and chlorine tablet distribution for sanitation. In Section 4.1.1, we describe how we estimated spatial and temporal distribution of the targeted refugees utilizing an analysis of the call record data of a major mobile network operator in Turkey and obtained the demand data for the identified three types of services. In Section 4.1.2, we describe how the potential service locations, the distances between each pair of locations, and the coverage data are obtained for each province. The number of mobile clinics, their service type capabilities and depot locations are specified in Section 4.1.3.

4.1.1. Demand data

As Syrian refugees working in seasonal agricultural jobs in Turkey migrate between provinces to work in the harvesting of agricultural products [3], the refugee intensity of a province increases during its agriculture season, which depends on the crops and location of the region. After identifying the service season, i.e. the planning horizon, of a province/region based on the agriculture season and the plans of the service provider, the number and locations of refugees that were in that region during the service season of the past year(s) forms the basis for the estimation of the amount and spatial distribution of the future demand of that region for such a mobile service during the upcoming service season.

A 2016 study by the UNHCR and Accenture found that 71% of world refugee households own a mobile phone [47]. Therefore, we utilized an analysis of mobile call data records of anonymous Syrians under temporary protection in Turkey (provided by Data for Refugees: The D4R Challenge on Mobility of Syrian Refugees in Turkey [14]) and examined the temporal and spatial dimensions of seasonal agricultural work to estimate the health care service needs to be provided by mobile health care teams. The D4R data analyzed in the current study consists of one set of base-station and another set of individual user level data. The Dataset 1 provides activity logs consisting of the number of incoming and outgoing calls and SMS messages for each of the 103,005 base stations on a daily basis between January 2017 and December 2017, where one can also identify the type of the area that the base station is located at. Accordingly, this dataset allows us to investigate how the share of the refugee activities within urban, suburban, rural, industrial, and seasonal areas of each province varied across different months of the year. We utilized this dataset to identify whether the over-time changes in the share of refugee activities in rural and seasonal parts of the provinces where seasonal agricultural activity is expected indicates an increased activity volume during the harvesting seasons of the main agricultural products cultivated in those provinces.

While the inspection of changes in the refugee activity volume in rural settings provided us with suggestive evidence for the existence of seasonal agricultural activity in the region, it did not allow us to infer whether the increased refugee activity in a rural setting is induced by increasing number of users or increasing number of calls or SMS activity per user. To overcome this shortcoming, we conducted a complementary analysis by utilizing the Dataset 2 that consists of fine-grained mobility data for randomly chosen refugee samples covering 15-day periods and provides the number of incoming and outgoing call and SMS activity logs for each refugee user on an hourly basis. As the refugee samples in this dataset are freshly chosen in every 15-day period, this dataset did not allow us to trace the same users throughout the year, but, the random sampling method utilized in the selection of the samples allowed us to trace the overtime changes in the total number of users in each province. Therefore, in our complementary analysis using Dataset 2, we identified the number of unique refugee users in the rural and non-rural areas of the provinces in regard, to estimate the number of SMFWs.

To investigate the internal migration patterns of the Syrian refugees, we utilized Dataset 3 that provides coarse grained mobile activity logs of 37,300 randomly selected refugees for the entire observation period of 2017. In this dataset, the spatial resolution of the activity logs was reduced by replacing base-station identifiers with 500 broader area identifiers called prefectures. Each refugee is assigned to a province for each month on the basis of his/her most frequently used prefecture location. The assignment procedure was done by considering the number of days that each refugee user had been active in each province. Accordingly, those refugees who had call activity in a single province throughout the month were assigned to that province, whereas those refugees who had call activities in more than one province throughout the month were assigned to the province where they had been active for highest number days. We further cleaned the dataset to include only those users with call activities in at least four months of the year, and this procedure yielded a total number of 24,233 unique refugee users to be included in the final dataset.

Since SMFWs spend most of their time during the day in the fields and it is almost impossible to know how the demand is distributed among the fields, the locations of the base-stations are considered as the demand points. This constitutes a close proxy to the real demand locations as the base-stations are densely dispersed throughout the areas under consideration. The harvesting season for the prevalent crop of Malatya lasts two months during July and August, therefore the planning horizon is identified as two months for the analysis of Malatya. The harvesting season for the main crop of Rize lasts three months during July, August, and September, therefore the planning horizon is identified as three months for the analysis of Rize. As an alternative analysis that considers probable restrictions of the service provider, we considered a planning horizon of one month for both provinces corresponding to the peak demand month (July for Malatya and August for Rize) and compared the results. We note that the problem is solved once in a year for the upcoming season. The number of demand points, i.e. $|J|$, for each province for varying season lengths is provided in Table 2.

For each province, we first obtained the number of distinct caller identifiers during the identified harvesting season for each base-station, i.e. demand point, from the dataset. As covering a point for a periodic service requires covering all of its demand throughout the planning horizon, if the planning horizon includes more than one month, for each demand point the maximum number of distinct caller identifiers among all months of the season is considered as demand. Other mobile network operators also provide telecommunication service to Syrians in Turkey. Under the assumption that the location-based distribution of refugee customers is similar for other mobile network operators, from the number of distinct caller identifiers for each base-station of the mobile network operator of concern, the intensity of refugees at each base-station is determined. The Directorate General of Migration Management (DGMM) of Turkey provides the percentage of children and women in the total number of Syrian refugees. Using this information, we estimated the seasonal demand of each base-station for three service types: (i) child-care and vaccination, (ii) reproductive health, and (iii) health education and chlorine tablet distribution for sanitation, which are referred to as S1, S2, and S3, respectively, in the following. Due to lack of data on the spatial distribution of children of SMFWs, we assumed a uniform distribution by associating the percentage of children in the refugee population with each refugee caller. Thus, the percentage of children, referred to as p_c%, multiplied by the estimated number of refugees is used to estimate the demand for the child-care and vaccination service type, i.e. service type S1, during the season. Likewise, due to lack of detailed data, the percentage of women multiplied by the estimated number of refugees is used to estimate the demand for the reproductive health service type, i.e. service type S2, during the season. Finally, $(1-p_c)/2$ multiplied by the estimated number of refugees is used to estimate the number of Syrian families, that is, the monthly demand for the health education and chlorine tablet distribution service type, i.e. service type S3, during the season.

Figs. 1 and 2 illustrate the locations of the demand points (blue stars) for one-month planning horizon for Malatya and Rize, respectively. It is seen that demand is more centralized in Malatya, whereas it is dispersed in Rize.

Table 2
The number of demand points, potential locations, and clinics for Malatya and Rize provinces.

Province	$\|T\|$	$\|J\|$	$\|L\|$	$\|K\|$
Malatya	1 month	66	108	7
	2 months	106	123	7
Rize	1 month	14	68	6
	3 months	18	68	6

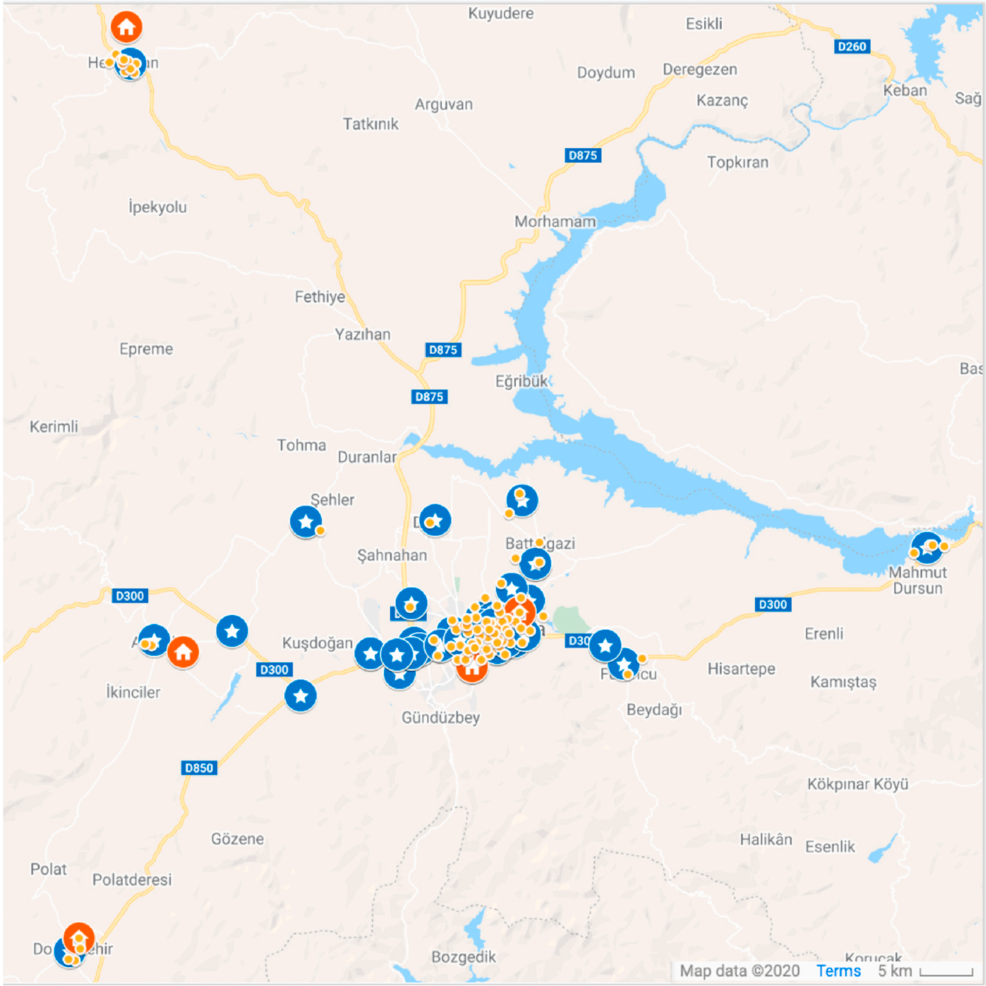

Fig. 1. The locations of the demand points (blue stars), potential locations (yellow points), and the clinics (red home icons) for one-month planning horizon for Malatya. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

4.1.2. Potential service locations, distance matrix and coverage data

For each province, the county, village and district centers are identified as candidates for potential service locations. The size of the set of candidate potential locations generated this way is very large compared to the number of demand points at the corresponding province. We eliminate some of the candidate locations based on their demand point coverage performance as explained later on.

The distance matrix between the demand points and the candidate potential service locations is generated using an open-source distance generation tool.

Based on public health expert consultation, the parameters l_{js} and e_{js} are set as follows. For each demand point, the coverage distances for each service type are identified as 1 km for the child-care and vaccination (S1) and reproductive health (S2) service types and 2 km for health education and chlorine tablet distribution (S3) service type. That is, $l_{j,1} = l_{j,2} = 1, l_{j,3} = 2, \forall j \in J$. A sensitivity analysis on the coverage distances for the service types for each province is performed in Sections 4.2 and 4.3. The maximum number of days between consecutive visits of each demand point for each service type is identified by our public health expert as: four weeks for child-care and vaccination (S1), two weeks for reproductive health (S2), and the number of days in the planning horizon for health education and chlorine tablet distribution (S3), i.e., just one visit is sufficient for S3.

The distance matrix together with the coverage distance limit for each service type s is used to generate a coverage matrix, a_{ijs}, for the corresponding service type. We, next, removed the candidate potential locations that cannot cover any demand point for the service type S1, i.e., the child-care and vaccination service, as the coverage distance of S1 is the tightest one.

Table 2 provides the number of potential locations for each province. Figs. 1 and 2 illustrate the potential locations (yellow points) for a one-month planning horizon for Malatya and Rize, respectively.

4.1.3. Clinics data

In current practice, a number of mobile clinics are based at the province centers and at some of the county centers, which have been pre-determined by a decentralized planning approach. In our analysis, the number, base (depot) location, service type, and maximum number of weekly working days of the mobile clinics are identified following the current practice. Table 2 provides the number of clinics for each province. Figs. 1 and 2 illustrate the depot locations of the clinics (red home icons) for one-month planning horizon for Malatya and Rize, respectively. We note that seven clinics of the Malatya province are located at five depot locations, where the two locations in the province center host two clinics each (see Fig. 1) and six clinics of the Rize province are located at five depot locations, where the location in the province center hosts two clinics (see Fig. 2). In current practice, in Malatya, one of the two clinics located at each of the two province centers is capable of providing service types S1 and S2 and the other can serve service type S3, and the remaining three clinics are located at different districts and are capable of providing all of the service types at the same time. In Rize, one of the two clinics located at the province center is capable of

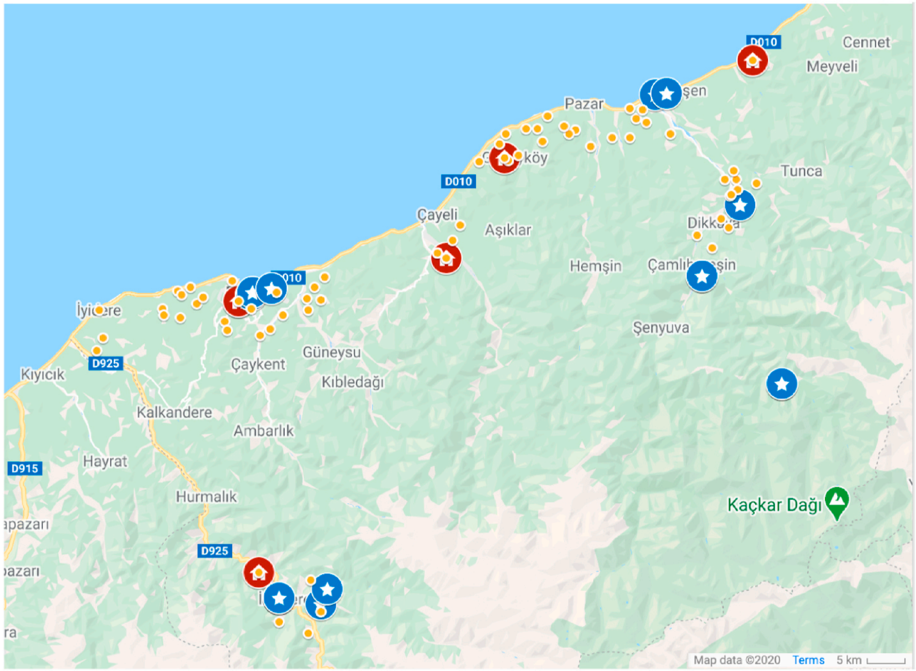

Fig. 2. The locations of the demand points (blue stars), potential locations (yellow points), and the clinics (red home icons) for one-month planning horizon for Rize. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

providing service types S1 and S2 and the other can serve service type S3, and the remaining four clinics are located at different districts and are capable of providing all of the service types at the same time.

The maximum traveling distance allowed from or to the depot location for a clinic, namely c, is set as 100 km for the first two models. The maximum number of days that each clinic can work in a week is set as 2 days, that is, $v_k = 2, \forall k \in K$. We also note that in our data each demand location requires all of the three types of services.

4.2. Analysis for Malatya

The harvesting season for apricots, the prevalent crop of Malatya, lasts two months during July and August and the number of refugees in rural areas increases during this period of the year as Fig. 3 illustrates. We performed two different analyses with planning horizon lengths of one month (twenty working days) and two months (forty working days) as follows.

First, the results obtained from the three models having three hierarchical objectives for each planning horizon length are reported (Sections 4.2.1 and 4.2.2). Next, we analyzed the trade-off between the coverage and the number of clinics objectives by implementing the augmented ε-constraint method to obtain efficient solutions for each province (Section 4.2.3).

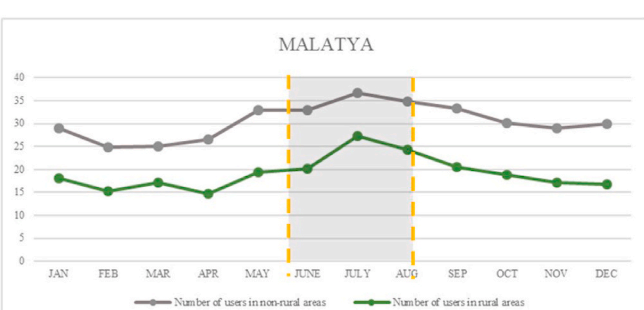

Fig. 3. The change in the number refugees in rural and non-rural areas for Malatya.

We evaluate and compare the results in terms of the number of clinics used, the coverage percentages for each service type, the total coverage percentage and the total run time of the models solved. Here, total coverage percentage shows total demand covered over all service types as a percentage of total demand for the three service types and hence is an aggregate measure.

During our analysis, starting from a coverage distance of 1 km for service types S1 and S2, and 2 km for service type S3, we gradually increased the coverage distances as shown in the first three columns of Table 3. For each triple of coverage distances, given the availability of seven clinics at different county centers, we first solved the model with the maximum coverage objective, i.e. **M1**, and then **M2** that has the minimum fleet size objective, using the maximum coverage values found by the first model. Finally, we solved **M3** to minimize total travel distance, using the maximum coverage and minimum number of clinics values found by the second model.

4.2.1. One-month planning horizon

The results of the analysis carried for one-month planning horizon are provided in Table 3. In Table 3 and in all other result tables provided in this article, for each coverage distance triple, the number of clinics utilized in the solutions, the coverage percentages for each service type, the total coverage percentage, the total travel distance values obtained from the three models and the run times of the three models are reported. We note that the coverage percentages for each service type and the total coverage percentage are the same in the results of all models, as the total coverage percentage is optimized in the first model and its optimal value is passed as a constraint to the other two models. Likewise, the number of clinics utilized is the same in the solutions of **M2** and **M3**.

According to the results in Table 3, with the tightest coverage distances, total coverage can be considered to be low. If refugees can travel longer distances to reach service, the coverage percentages increase, however, still nearly 10% of refugees remain far from the clinic stops even with the loosest coverage distances. While the first model utilizes all of the 7 clinics for all coverage distance triples, the second model reduces the number of clinics used by at least two. This result illustrates that considerable savings can be achieved by the hierarchical

Table 3
Results of the one-month Malatya case obtained from models **M1**, **M2** and **M3**.

Coverage dist. (km)			No. of clinics used		Total coverage	Total traveling distance			Max. dist. (km)	CPU sec		
S1	S2	S3	M1	M2	(%)	M1	M2	M3	M3	M1	M2	M3
1	1	2	7	5	81.53	2427.38	2427.38	1397.62	85.11	7	17	20
2	2	3	7	4	89.19	2962.4	2962.4	1298.48	84.37	15	81	36
2	2	4	7	4	90.39	3099.78	3099.78	1199.22	84.37	28	161	39
3	3	4	7	4	90.58	2488.42	2488.42	1138.76	84.37	31	226	61
3	3	5	7	4	90.58	1809.74	1809.74	911.42	84.37	36	302	66
Avg. Impr. by M2 (%)				40	Avg. Impr. by M3 (%)			52.76				

optimization approach. Namely, two of the seven available clinics of Malatya province are not utilized for tightest coverage distances and three of them are not utilized for the remaining triples of coverage distances; hence indicating a significant level of savings. Figs. 4 and 5 show the visited locations originating from the depot location for each clinic with a different color for the tightest and second tightest coverage distance triples, respectively. The city center of Malatya is shown with a red star. Malatya has two province centers. Four of the seven clinics are based at the province centers. The results show that one of the two clinics based at the two locations in the province centers are not used for the tightest coverage distance triple (see Fig. 4). For the second tightest coverage distance triple, three of four clinics based at the province centers are not used (see Fig. 5). Furthermore, the total travel distance values in the solutions of models **M1** and **M2** are reduced significantly (by 53% on the average over 5 tested instances, as seen in the last row of Table 3) in the solutions of **M3**, which are the final suggested solutions. All of these results demonstrate the importance of providing clinic service from dispersed locations as a result of centralized planning by following a system-wide optimization approach.

4.2.2. *Two-month planning horizon*

Next, we increase the planning horizon length to two months. As Table 2 specifies, the number of demand points and the number of potential locations increase to 106 and 123, respectively, for a two-month planning horizon. The results of the analysis for this case are provided in Table 4.

According to the results in Table 4, for each coverage distance triple, the required number of clinics does not change compared to that of the solution for one-month planning horizon. For all coverage distance triples, the total coverage percentage and the coverage percentage of service type S3 increase when the planning horizon becomes two months. However, the coverage percentages of service types S1 and S2 increase for only the tightest coverage distance triple and decrease for the remaining. It is observed that the coverage percentages for service types S1 and S2 are stuck in the band between 80% and 86% and do not go beyond the 87% border. This is due to the more dispersed structure of the demand points for two-month planning horizon compared to that of the one-month planning horizon. Comparing the run times presented in Table 4 with those for the Malatya case having one month planning horizon provided in Table 3, we see that with the increase in the problem size, the run times increase more than five hundred-fold. Although the

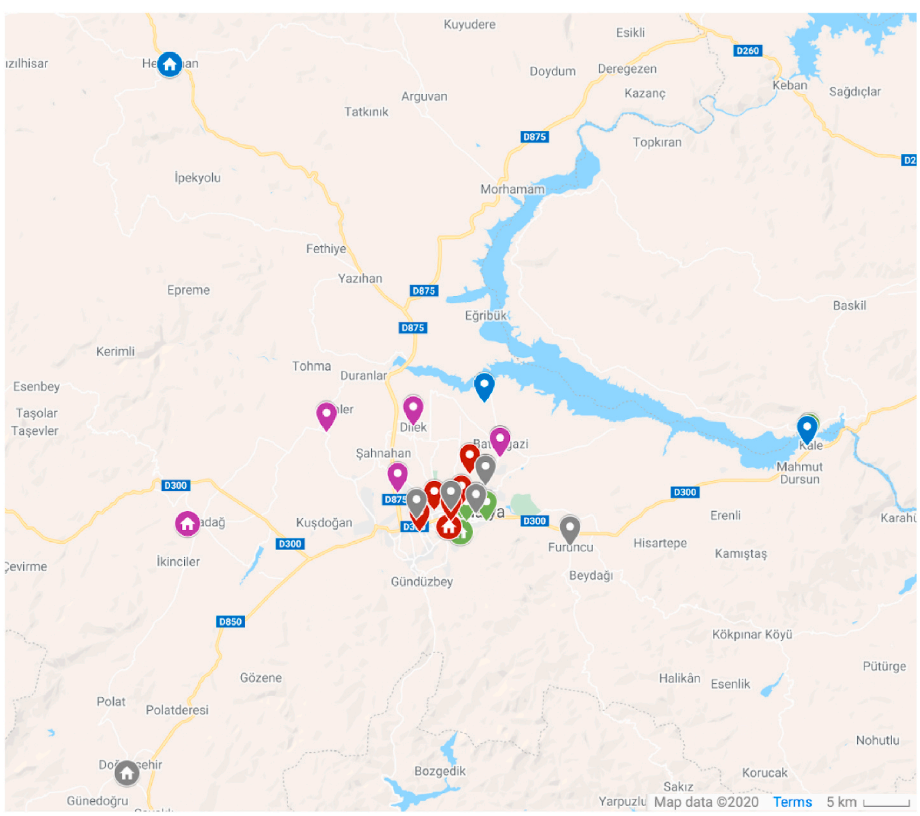

Fig. 4. Depot locations and visit points of the utilized five clinics (each in different color) for Malatya with coverage distances of 1 km for S1 and S2, 2 km for S3. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

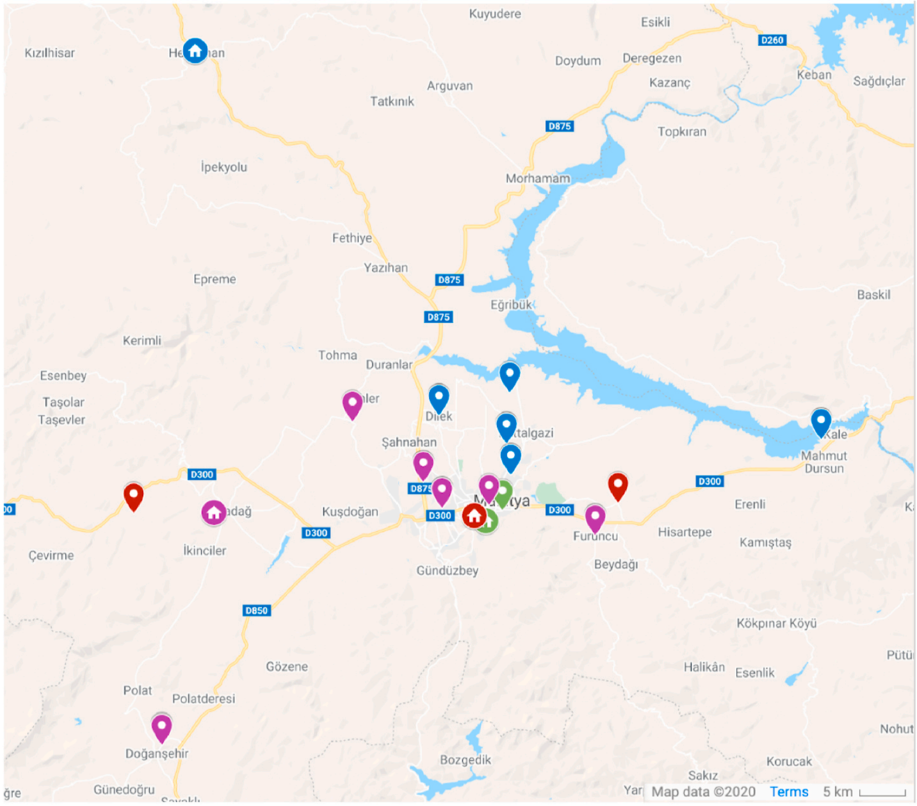

Fig. 5. Depot locations and visit points of the utilized four clinics (each in different color) for Malatya with coverage distances of 2 km for S1 and S2, 3 km for S3. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 4
Results of the two-month Malatya case obtained from models **M1**, **M2** and **M3**.

Coverage dist. (km)			No. of clinics used		Total coverage	Total traveling distance			Max. dist. (km)	CPU sec		
S1	S2	S3	M1	M2	(%)	M1	M2	M3	M3	M1	M2	M3
1	1	2	7	5	89.18	5028.06	5028.06	3045.12	53.77	17177	29970	38
2	2	3	7	4	91.84	6474.46	6474.46	1919.6	41.17	36481	33989	99
2	2	4	7	4	91.84	6695.08	6695.08	1919.6	53.77	31948	40683	113
3	3	4	7	4	91.94	7959.64	7959.64	1590.96	53.77	13524	51008	115
3	3	5	7	4	91.94	7747.22	7747.22	1590.96	53.77	24179	46407	121
Avg. Impr. by M2 (%)				40	Avg. Impr. by M3 (%)			68.12				

longest run of any of the three models of the instances with one month planning horizon takes less than 6 min, the run times of the models **M1** and **M2** for the instances having a planning horizon of two months ranges from 3.76 to 14.17 h. Nevertheless, since the plan is made in advance for the upcoming two months, the run time can still be considered reasonable. If we compare the solutions of the three models that are solved back to back, we observe that we can save 40% on the average from the number of clinics used compared to the current decentralized planning approach. We also see that we can reduce the total traveling distance by 68% on the average by choosing the visit points in an optimal fashion while still maintaining high coverage levels and using a minimum number of clinics.

4.2.3. One-month planning horizon with bi-objective approach

To analyze the trade-off between the first two critical objectives, we adopted the augmented ε-constraint method, which is widely used for multi-objective optimization problems [e.g. 48, 49]. For a bi-objective optimization problem, the ε-constraint method, proposed by Berube et al. [50], transfers one objective into the ε-constraint added to the model, gradually reducing the value of ε and solving a sequence of single objective optimization problems to obtain a set of non-dominated solutions [51]. In the augmented ε-constraint method, the slack or surplus variables added for the ε-constraint are used as a second term (with lower priority in a lexicographic manner) in the objective function, forcing the program to produce only efficient solutions [49].

Taking the gradual reduction value in the first objective (total coverage) as 1% and the multiplier of the surplus of the ε-constraint corresponding to the total coverage percentage objective as 0.01 in the second objective (the number of clinics used), we generated a set of non-dominated solutions for varying service distances for a one-month planning horizon. For each triple of coverage distances, the non-dominated solutions except the ones that have zero objective value for both objectives are reported in Table 5. To illustrate the results in Table 5, Fig. 6 shows the solutions on the Pareto frontier depicting the total coverage percentage versus the number of clinics used for varying distance limit triples.

According to the results in Table 5, for each coverage triple, non-dominated solutions are generated using a step size of 1% in the augmented ε-constraint method. For all coverage distance triples, for the highest coverage levels, a small compromise in coverage percentage leads to one less number of clinics used. We want to also note that for the non-dominated solutions that do not reach the highest coverage

Table 5
The non-dominated solutions for one-month Malatya model for varying coverage distances for each service type.

Coverage distance (km)			No. of	Total coverage	Coverage per service type (%)			CPU
S1	S2	S3	clinics used	(%)	S1	S2	S3	sec
1	1	2	5	81.53	76.01	76.1	89.08	20
			4	80.92	75.63	75.77	88.1	41
			3	80.1	74.82	75.07	87.15	32
			2	77.88	72.5	72.11	85.75	32
			1	68.75	62.45	62.22	77.72	23
2	2	3	4	89.19	88.98	89.08	89.38	174
			3	88.21	88.11	88.04	88.41	282
			2	87.39	87.03	87.07	87.84	418
			1	84.84	84.44	84.81	85	316
2	2	4	4	90.39	88.98	89.08	92.25	137
			3	89.41	88.11	88.04	91.28	318
			2	88.73	87.25	87.05	90.99	244
			1	85.62	84.44	84.23	87.49	323
3	3	4	4	90.58	89.36	89.37	92.25	121
			3	89.56	88.43	88.34	91.23	481
			2	88.57	87.36	87.40	90.20	544
			1	85.92	84.98	84.37	87.87	286
3	3	5	4	90.58	89.36	89.37	92.25	122
			3	89.62	88.49	88.34	91.35	458
			2	88.63	87.57	87.46	90.22	447
			1	85.92	84.98	84.37	87.87	236

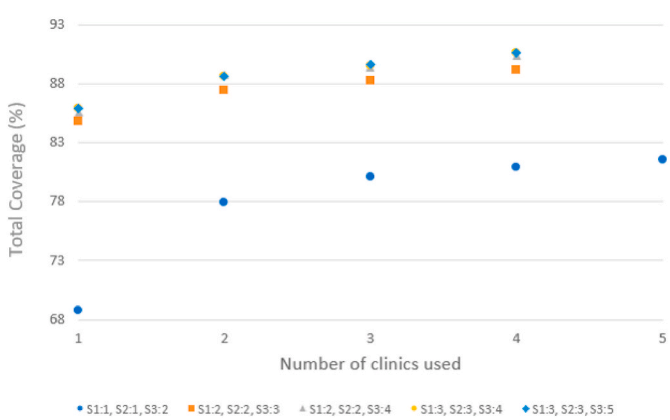

Fig. 6. The Pareto frontier of the total coverage percentage versus the number of clinics used for varying distance limit triples.

percentages for the corresponding triple, the clinics used are not the ones that are based at the two province centers. This underlines the importance of providing clinic service from distributed base locations together with centralized planning once more.

Fig. 7 illustrates the solutions on the Pareto frontier depicting the coverage percentages for each service type versus the number of clinics used given a 1 km distance limit for S1 and S2, and a 2 km distance limit for S3. Since the coverage distance limit of S3 is larger compared to those of S1 and S2, the Pareto frontier of S3 is above those of the others as expected.

4.3. Analysis for Rize

The harvesting season for tea, which is the main crop in Rize, lasts three months during July, August, and September and the data analysis shows that the number refugees in rural areas increases during this period of the year as Fig. 8 illustrates. Therefore, we analyzed the case with a planning horizon length of three months (sixty working days) considering the demand from July to September. In addition, as the peak in demand is observed during August, we analyzed the case with a

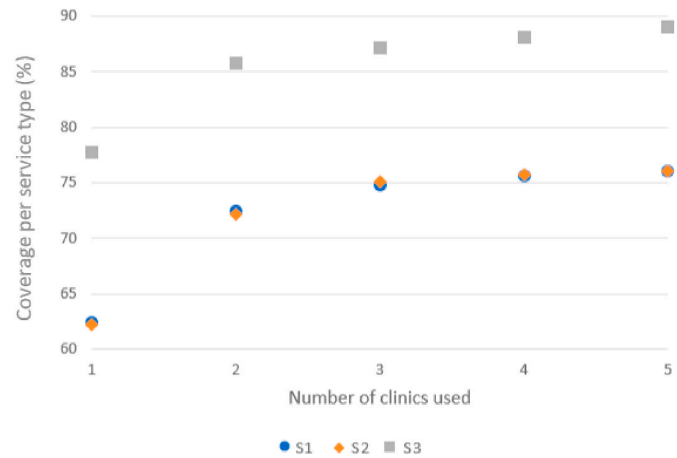

Fig. 7. The Pareto frontier of the coverage percentages for each service type versus the number of clinics used for distance limits: S1=S2=1 km, S3 = 2 km.

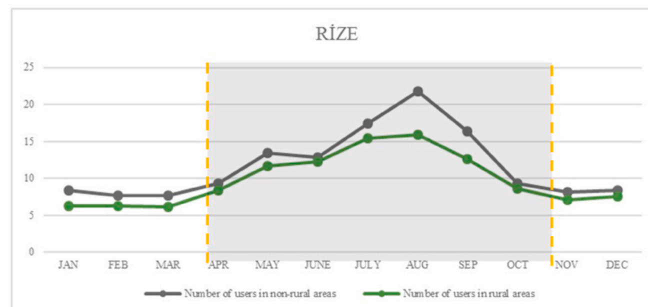

Fig. 8. The change in the number refugees in rural and non-rural areas for Rize.

planning horizon length of one month (twenty working days) considering the demand of August in Appendix A.

Similar to the analysis on Malatya, in our analysis on Rize we gradually increased the coverage distances and for each triple of coverage distances, given the availability of six clinics at different county centers, we first solved the model with the maximum coverage objective and then with the minimum fleet size objective given the maximum coverage limits found by the first model. Then, we optimize the total travel distance in the third step, while still keeping the maximum coverage limits and making sure that the minimum number of clinics are used. As in the Malatya cases, we suggest the use of the solution to the third model.

The demand points of different months of the harvesting season do not differ so much for Rize. As Table 2 shows, for a three-month planning horizon, the places and the number of potential locations remain the same and only four additional demand points are included compared to the case for a one-month planning horizon. The results of the analysis carried for the three-month planning horizon are provided in Table 6.

According to the results in Table 6, for all coverage distance triples, the required number of clinics is now two. For all coverage distance triples, especially for the tightest coverage distance triple, the coverage percentages increase when the planning horizon becomes three months. However, for the tightest coverage distance triple, nearly 8% of the service demand for S1 and S2 remain unserved even with increased number of clinics. As the problem size does not increase much when the planning horizon length triples, the run times are still less than 1 min but yet increased nearly ten-fold compared to the case for one-month planning horizon.

In Appendix A, we also analyze the trade-off between the first two objectives for the three month planning horizon case of Rize.

Table 6
Results of the three-month Rize case obtained from models **M1**, **M2** and **M3**.

Coverage dist. (km)			No. of clinics used		Total coverage	Total traveling distance			Max. dist. (km)	CPU sec		
S1	S2	S3	M1	M2	(%)	M1	M2	M3	M3	M1	M2	M3
1	1	2	6	2	94.46	3302.42	3302.42	1522.2	26.53	1	13	16
2	2	3	6	2	99.45	5458.44	5458.44	1515.9	24.84	1	28	268
2	2	4	6	2	99.45	3965.88	3965.88	1516.02	24.84	1	22	4
3	3	4	6	2	100	6390.52	6390.52	1283.96	24.84	1	23	70
3	3	5	6	2	100	5209.98	5209.98	1284	24.84	1	22	45
Avg. Impr. by M2 (%)				66.67	Avg. Impr. by M3 (%)			68.63				

5. Conclusions

Agriculture has emerged as a promising sector for Syrian refugees in Turkey for generating income. Minimizing the hazards for Syrian refugees involved in agriculture requires on site services such as health care and there are efforts to train health professionals coming from Syria to be employed in mobile health services [52]. Nevertheless, these services still depend on the constrained resources of provincial health directorates. In order to provide the most beneficial service with the most efficient use of the resources, using various types of data, such as mobile call records, provides a great opportunity to maximize the coverage of health services including reproductive and child health, health education, immunization, and water sanitation for SMFWs who have limited access to such services. While keeping the maximum reachable population as a target level, it is also possible to allocate the optimal number of clinics to the service origins. Hence, the best possible service level can be maintained by the most efficient use of the resources.

There are several challenges in the implementation of mobile health services. Among these, program logistics and frequent movement of farm-workers make it difficult to optimize the service provision. However, our data analysis reveals the locations of SMFWs over time and thus enables bringing the services close to the actual SMFW concentrations by a mathematical model, thereby maximizing the people that can get service within small distances. A second binary integer programming model guides the decision makers to identify the required number of clinics to be based at different counties, while achieving the maximum service coverage throughout the province. Furthermore, a visit schedule is generated for these clinics for the harvesting season with reasonable computational effort via our data-driven optimization approach. We note that distribution of information via text messages sent to mobile phones of Syrian refugees about the mobile service schedule and locations can improve access, which can in return help improve coverage levels.

Our case study results, using the data for two provinces carrying different characteristics over different planning horizons, including a bi-objective analysis, show that with a small compromise in demand coverage levels and assured distances to the locations where SMFWs accommodate or work, the resources can be used much more efficiently and based at more beneficial locations. The results demonstrate the superiority of the centralized planning approach compared to the current practice in terms of resource usage.

While our case study illustrates the use of the proposed model to support decision making in the context of provision of health care to seasonal migrant farm workers, it can be used for other types of mobile services that require several visits throughout a planning horizon, once the demand at different locations have been estimated.

Several extensions of the presented models are possible future work topics. For instance, the presented mathematical model can be extended with the consideration of equity among the demand points in terms of variance among the travel distances to the clinic service locations. Another direction of extension is to assign an adequate number of personnel to the clinics according to the demand magnitude at different locations. Then, the capacity of the clinics can be accounted for and become a decision in the model. Another possible future work direction is to align the duration of stay of the clinics with the demand magnitudes. That is, the clinics may stay longer at locations that have higher demand, and shorter at others. For instance, the demand points can be classified as high demand and low demand locations and accordingly, the clinic may stay half a day at low demand locations, and a full day at high demand locations. This may lead to better utilization of the resources.

Author statement

Sibel Salman: Conceptualization, Methodology, Writing. Eda Yucel: Methodology, Data curation, Software, Writing. Ilker Kayi: Conceptualization, Writing. Sedef Turper-Alisik: Data curation, Writing. Abdullah Coskun: Data curation, Visualization.

Declaration of competing interest

None.

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AppendixA. Additional analysis for Rize

AppendixA.1. Three-month planning horizon with bi-objective approach

In order to analyze the trade-off between the two objectives for Rize, we adopted the augmented ε-constraint method to generate the non-dominated solutions for varying service distances. We set the gradual reduction value in the first objective (total coverage) to 1% and the multiplier of the surplus of the ε-constraint corresponding to the total coverage percentage objective to 0.01 in the second objective (the number of clinics used). The obtained non-dominated solutions except the ones having zero objective value for both objectives for each triple of service distances are reported in Table A.7.

Table A.7
The non-dominated solutions for three-month Rize model for varying coverage distances for each service type

Coverage distance (km)			No. of	Total coverage	Coverage per service type (%)			CPU
S1	S2	S3	clinics used	(%)	S1	S2	S3	sec
1	1	2	2	94.46	92.34	92.12	99.22	12
			1	89.91	87.81	87.38	94.72	4
2	2	3	2	99.45	99.21	99.16	100	26
			1	94.48	94.23	94.27	95.02	21
2	2	4	2	99.45	99.21	99.16	100	26
			1	95.29	94.52	94.38	95.29	6
3	3	4	2	100	100	100	100	26
			1	96.31	96.46	95.77	96.34	23
3	3	5	2	100	100	100	100	26
			1	96.33	96.15	96.13	96.73	19

According to the results in, Table A.7 for all coverage distance triples, there are two non-dominated solutions found and a small compromise of 5% in coverage percentage limits leads to one less clinic used. Similar to the Malatya case, for the non-dominated solutions that do not reach the largest coverage percentages for the corresponding triple, the clinics used are not the ones that are based at the province center.

AppendixA.2. One-month planning horizon

The results of the analysis carried for one-month planning horizon are provided in Table A.8.

Table A.8
Results of the one-month Rize case obtained from models **M1**, **M2** and **M3**

Coverage dist. (km)			No. of clinics used		Total coverage	Total traveling distance			Max. dist. (km)	CPU sec		
S1	S2	S3	M1	M2	(%)	M1	M2	M3	M3	M1	M2	M3
1	1	2	4	1	91.99	827.1	827.1	643.92	44.91	1	1	2
2	2	3	6	2	99.37	1164.38	1164.38	405.98	22.43	1	1	1
2	2	4	6	2	99.37	1005.36	1005.36	405.98	22.43	1	1	1
3	3	4	6	2	100	1534.52	1534.52	328.64	22.43	1	1	1
3	3	5	6	2	100	1002.72	1002.72	328.64	22.43	1	1	1
Avg. Impr. by M2 (%)				68.33	Avg. Impr. by M3 (%)			58.54				

According to the results in Table A.8, if refugees can travel one km longer to reach service, the coverage percentages get close to 100%. A remarkable observation is that for the tightest coverage distance triple, one clinic (which is not based at the province center) is sufficient to reach the largest possible coverage percentages, whereas if refugees can travel one km longer distances, then two clinics (which are not based at the province center as well) are required to cover nearly all of the total demand. As it is observed in the results of Malatya, the first model utilizes much more clinics compared to the second model to achieve the same total coverage percentage. On the average over the five instances, the fleet size is reduced by 68%, whereas the total travel distance is reduced by 58%. Fig. A.9 and A.10 illustrate the visit points selected for the routes originating from the depot location of each clinic with a different color for the tightest and second tightest coverage distance triples, respectively. The city center of Rize, which also corresponds to the province center, is shown with a red star. As it can be seen in both figures, according to our proposed solutions, the clinics located in the province center need not be used for service, despite the current practice.

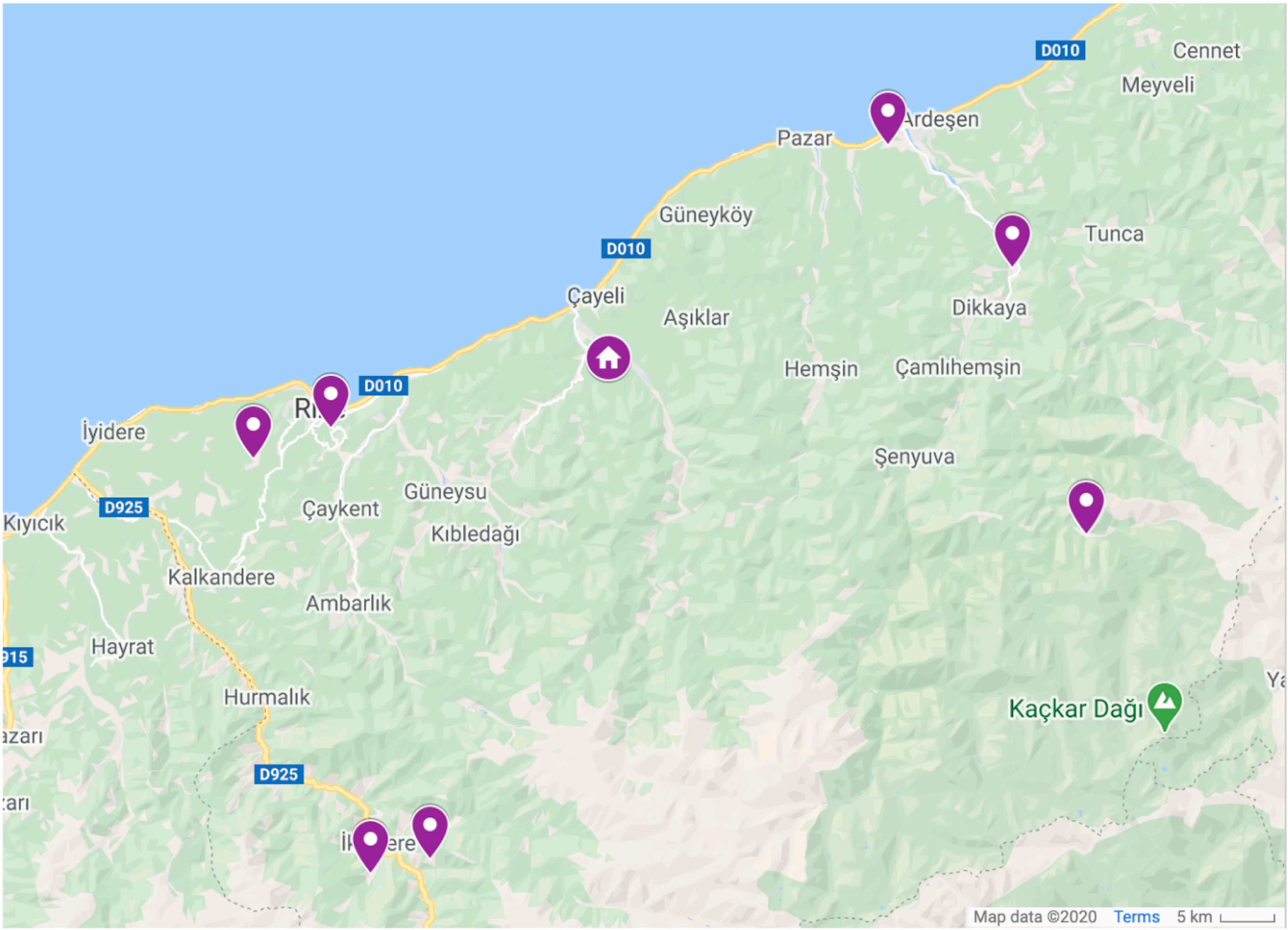

Fig. A.9. Depot locations and visit points of the utilized clinic for Rize with coverage distances of 1 km for S1 and S2, 2 km for S3

Fig. A.10. Depot locations and visit points of the utilized two clinics for Rize with coverage distances of 2 km for S1 and S2, 3 km for S3

AppendixA.3. One-month planning horizon without one dominating demand point

We observed that one of the demand points constitutes nearly 80% of the total service demand of the province. This demand point corresponds to Ayder, which is a summer resort with no settled population. Ayder hosts visitors during the summers and most likely the refugees work in the tourism sector there. Next, we performed an analysis excluding that demand point to observe how the results would change. The results are provided in Table A.9.

Table A.9
Results of the one-month Rize case without the dominating demand point (Ayder) obtained from models **M1**, **M2** and **M3**

Coverage dist. (km)			No. of clinics used		Total coverage	Total traveling distance			Max. dist. (km)	CPU sec		
S1	S2	S3	M1	M2	(%)	M1	M2	M3	M3	M1	M2	M3
1	1	2	6	1	48.91	863.56	863.56	643.92	41.44	1	1	1
2	2	3	6	2	95.98	1958.02	1958.02	405.98	22.43	1	1	1
2	2	4	6	2	95.98	875.22	875.22	405.98	22.43	1	1	1
3	3	4	6	2	100	1027.76	1027.76	328.64	22.43	1	1	1
3	3	5	6	2	100	972.04	972.04	328.64	22.43	1	1	1
Avg. Impr. by M2 (%)				70	Avg. Impr. by M3 (%)			58.51				

According to the results in Table A.9, if Ayder is excluded, the coverage percentages decrease by an important amount for all coverage distance triples, especially for the tightest coverage distance triple. It is due to the dispersed structure of the demand points in Rize. On the other hand, the results show that traveling only one km longer to reach service results in a considerable improvement in receiving service for SMFWs.

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