Mobile Vaccination Clinic Routing Problem

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Abstract

Accessing Covid-19 vaccines may be challenging for people with disabilities, the elderly, which are particularly vulnerable to the adverse effects of Covid-19 disease, and the population in rural areas. The utilization of mobile vaccination clinics is studied in this paper to overcome this challenge. A mathematical model is proposed to route mobile vaccination clinics over a network consisting of a depot, candidate stops, and demand points. Different service levels are considered to ensure that the mobile vaccination clinic is located within a given distance of demand points. The population at demand points is divided into priority groups with varying criticalities and requirements for service levels. An extension to the location routing problem is proposed and an integer linear model is presented that optimizes the routes and stopping points of the mobile vaccination clinics. The objective is to maximize the coverage of prioritized groups while providing high service levels. A case study based on Van province in Turkey is conducted to analyze the proposed solution method. The preliminary results indicate a tradeoff between the prioritization of groups and the network-level effectiveness of the solution.

Keywords
Covid-19, Healthcare, Mobile Clinic, Location-Routing, and Vaccine.

1. Introduction
Covid-19 has claimed its place in history as one of the deadliest pandemics with 243,857,028 cases and 4,953,246 deaths in total as of October 24th, 2021 (WHO 2021). The fast discovery and implementation of vaccines have drastically decreased the infectious and mortality rates, especially in developed countries, however, many countries have struggled with the fast administration of vaccines. According to Ritchie et al. (2021), only 3.1% of the population in low-income countries received at least one dose of vaccine. The elderly, which are vulnerable to the adverse effects of the Covid-19 disease have faced difficulties in accessing vaccines in many parts of the world. Lack of transportation options, immobility, and increased infection risk at the healthcare centers have caused fewer vaccines to be administered to these groups. Similar issues also arise for the group of the population that live in remote areas with no healthcare centers nearby. Georgia Health Policy Center (2021) states that two of the key problems on vaccinating the population in rural areas are regarding limited supply and accessing patients, and they propose mobile strategies as a part of the solution. To overcome the immobility and remoteness issues, mobile vaccination clinics and teams were utilized in many countries in the past months including the USA (MDH 2021, CDPHE 2021) and Turkey (Kaya 2021, TRTHaber 2021, Yildiz 2021, Bayram 2021).

The utilization of mobile vaccination clinic provides the ability to be vaccinated near one's home and allows the immobile groups of the population to receive their vaccines. It is also beneficial for the groups that are vulnerable to the disease since getting vaccinated at a mobile healthcare clinic reduces the risk factors in regular healthcare facilities. Using mobile healthcare clinics also allows access to remote areas and broadens the reach of healthcare providers, but unfortunately, adds more complexity to the vaccination process as computing the routes and the stops to be visited is necessary.

In this paper, a system is considered in which there is a depot, candidate stops, demand points, and multiple priority groups at each demand point. An integer linear programming (ILP) model is proposed to determine the daily routes of mobile vaccination clinics, as well as the service time at each stop, and the number of people to be vaccinated from each group. The objective of the proposed model is to maximize the weighted number of vaccinated populations. The model also seeks to balance the tradeoff between the prioritization of the groups and the total coverage level that can be achieved in the network. The implementation of this model is illustrated in a case study that focuses on a rural area.

The rest of this document is organized as follows. In Section 2, the related literature is briefly reviewed. In Section 3, the problem is defined and the ILP model is presented. In Section 4, the case study data is presented and the preliminary results are discussed, and in Section 5, concluding remarks are provided.

2. Literature Review

The literature related to healthcare systems has gained more attention recently with the problems that arose with the Covid-19 pandemic. This work closely relates to studies that focus on mobile healthcare applications. One of the mobile healthcare applications focuses on providing home healthcare services. Fikar and Hirsch (2017) provide a categorical review of the home healthcare problem, where Cinar et al. (2021), Liu et al. (2019), Benzarti et al. (2013), Fikar and Hirsch (2015), and Bertels and Fahle (2006) propose different solution algorithms to variations of this problem. The routing problem of mobile vaccination clinics holds similarities with home healthcare problems in terms of objectives, such as coverage of critical patients and service level, however, the problem discussed in this paper has different aspects, such as the lumpy and vast demand, and perishability of the vaccine in the mobile vaccination clinic routing problem. A similar problem in the literature is the bloodmobile routing problem studied by Rabbani et al. (2017), Sahinyazan et al. (2015), Bashiri and Ghasemi (2018), Gunpinar and Centeno (2016), and Ramirez et al. (2018), where the demand uncertainty is commonly considered. Routing for bloodmobiles and vaccination clinics are different in terms of time horizon, where a longer time horizon is usually considered while routing the bloodmobiles. Additionally, in contrast to the bloodmobile routing problem, deterministic demand is considered in the mobile vaccination clinic routing problem. The closest category to the problem in this study is the mobile healthcare clinic routing problem. Yucel et al. (2018) propose a data-driven algorithm where Salman et al. (2021) and Doerner et al. (2007) focus on providing healthcare services in rural and non-developed areas by utilizing mobile clinics. Cakir et al. (2021) consider a mobile vaccination clinic for Covid-19 without the priority group distinction.

Since the route and the stopping points among candidate locations of the mobile vaccination clinics are considered at once in this study, the problem can be categorized as a location routing problem (LRP). This problem has been studied widely and there is a broad literature in this field, extensively analyzed by Prodhon and Prins (2014), and Drexl and Schneider (2015). Belenguer et al. (2011), Contardo et al. (2014), and Ponboon et al. (2016) proposed exact algorithms to solve standard LRP and its variants, where metaheuristics and matheuristics were proposed by Rybickova et al. (2019), Li et al. (2006), Yu et al. (2010) and Marinakis et al. (2015).

The problem discussed in this study differs from the aforementioned studies with the prioritization of certain population groups and service levels, where the service level is defined as the proximity of candidate stops to demand points, and also the resulting discussion on the tradeoff between the prioritization of the groups and the total coverage level that can be achieved.

A related field to this study is the prioritization of population groups for vaccination. It is common to prioritize certain groups over others considering occupational criticality, vulnerability towards disease, and contact rates within and among groups for Covid-19 vaccination. Foy et al. (2021), Li et al. (2021), and Bubar et al. (2021) analyze the effect of prioritizing different groups on different performance metrics, where detailed compartmental models are proposed in Chen et al. (2020), Dalgic et al. (2017), and Mylius et al. (2008). In the case study presented in this paper, the prioritization of groups is based on both vulnerabilities towards Covid-19, and the immobility of groups.

To summarize, due to the decision factors and the structure of the problem, it is considered as a subcategory of LRP, which is a topic with a vast amount of literature. There exist several studies in the literature about home healthcare services, bloodmobile routing, and healthcare clinic routing that closely relates to this study. However, there are some differences between this study and the existing literature in terms of the distinctive features of Covid-19 vaccination operations, such as the lumpy demand and different characteristics of the population groups to be vaccinated. The prioritization of population groups for the Covid-19 vaccination is also a considerably new and evolving research area with several contributions so far and was also considered in this paper as an important factor for the vaccination decisions. This study contributes to the literature with a new ILP model that combines the mobile healthcare systems with important characteristics of Covid-19 disease, by considering the criticality and immobility of the population to be vaccinated. It is aimed to provide insights for the healthcare authorities on the possible results of utilizing mobile vaccination clinics on coverage levels, especially in rural areas.

3. Methods
In this section, first, the problem is described and then the ILP model is presented.

3.1 Problem Description
A mobile vaccination clinic routing problem (MVCRP) is presented in this paper over a network consisting of a depot, candidate stops, and demand points. Given these candidate stops, it is aimed to construct the route of the mobile vaccination clinic that starts from and ends at the depot. It is assumed that the mobile vaccination clinic has all required resources, such as necessary equipment, and staff (i.e. nurses) to administer the vaccines. The route is determined for one working day. Each mobile vaccination clinic is assumed to contain refrigerators for the cold chain requirements of the vaccines, and the refrigerators' capacities limit the total number of vaccines that can be administered within a day. If multiple mobile vaccination clinics are routed in a large region, it is presumed that the region is clustered considering the characteristics of demand points, distance, or other important aspects for the authorities and that each clinic is assigned to a specific cluster. The candidate stops are determined such that there is at least one candidate stop near each demand point in the network.

In MVCRP, the vaccination demand for each priority group at each demand point is assumed to be known, and once the route is finalized, an appointment will be scheduled for the population that is to receive the vaccination at each stop. The possibility of no-shows is not considered in this study. The service level is defined as the proximity of the demand points to candidate stops, and this level is determined by a maximum distance threshold. It specifies the quality of service provided to the demand points, where stopping at locations that is closer to the demand points result in a higher service level. Service levels vary for each priority group according to its immobility level. For example, since the disabled population may not be able to travel far from their residency, they are provided with a lower distance threshold, where the other groups can be served by further points. It is more valuable to provide higher service levels to prioritized groups. A network example is represented in Figure 1, where the network comprises 7 candidate stops, 3 demand points, 2 priority groups, and a depot. Varying service levels are also shown in Figure 1 for different priority groups.

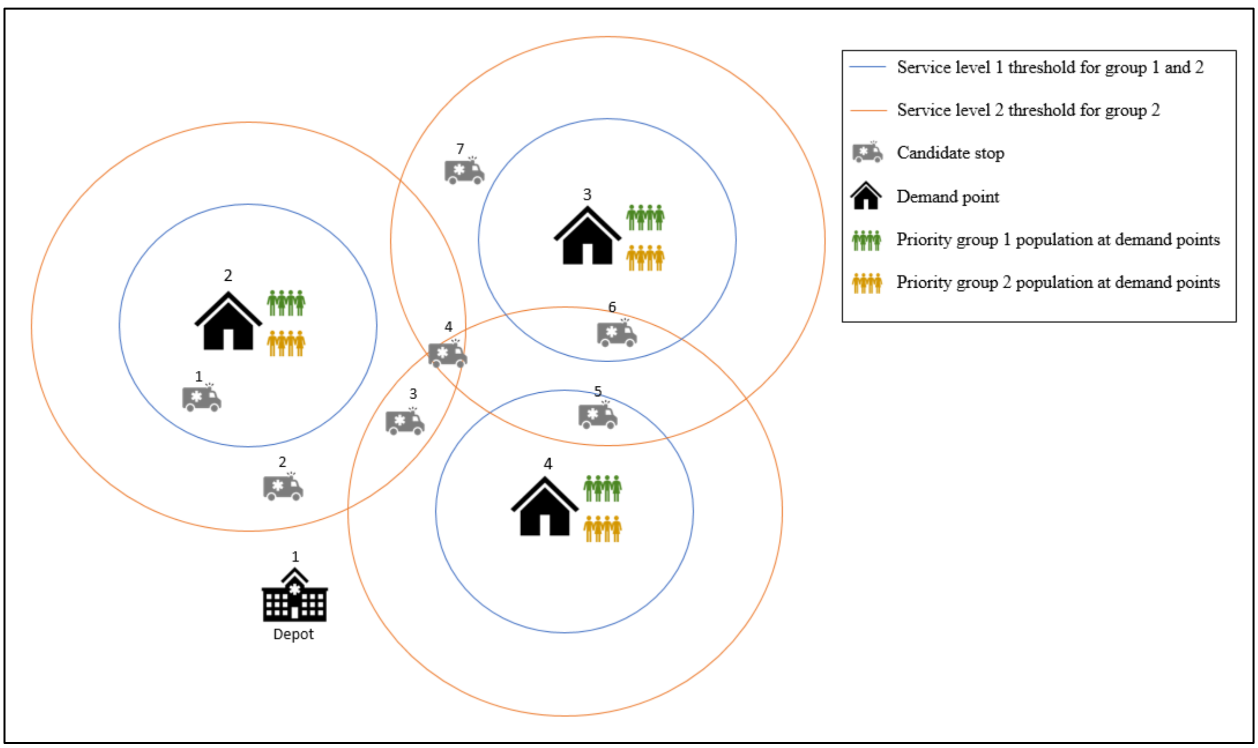

Figure 1: An exemplary network for MVCRP for two priority groups and varying service levels

The routes for mobile vaccination clinics are determined within a fixed period for a day. The factors that define the total route duration are the travel times between the locations of the stops, and the service time at each selected stop. Service times at stops are based on a fixed time required for the setup for each departure from of mobile vaccination clinic, the waiting time for the last patient in case of an allergic reaction, and the variable vaccination time. Vaccination time is dependent on the number of people that will be vaccinated, and the number of nurses that are assigned to the mobile vaccination clinic. The fixed service time and travel time cause a tradeoff between the prioritization of groups and the effectiveness of the vaccination route. That is, routing the clinic to multiple stops and providing vaccinations at those points might increase the coverage level of prioritized groups, however, due to the time spent on relocating the clinic, a fewer number of people might receive vaccination in total.

Solving this problem can support the roll-out of Covid-19 vaccination in different urban and rural settings. For example, mobile clinics can be used to vaccinate populations that cannot access existing vaccination clinics (such as the closest hospital or family health center) due to lack of sufficient health care resources or immobility of population groups. In such cases, the prioritization of population groups may be based on their immobility in addition to their vulnerability to the disease. Moreover, this problem can be solved for the implementation of an at-home vaccination system, where the mobile vaccination clinic stops at a candidate location, but the nurses walk to the demand points to vaccinate the immobile population at home.

In Section 3.2, the ILP model is proposed to construct the routes of mobile vaccination clinics, and the number of people to vaccinate from each priority group with each service level.

3.2 Mathematical Model

The model's parameters and decision variables are introduced as follows.

Sets

I: set of demand points
P: set of demand priority groups
N: set of candidate stops
L: set of service levels

Parameters

d_{ip}: demand of priority group $p \in P$ at demand point $i \in I$
b: time required to vaccinate one person
w: fixed setup time and waiting time required after the vaccine is administered at each stop
V: capacity of the mobile vaccination clinic
α_l: coverage level weight for level $l \in L$
r_p: priority weight for priority group $p \in P$
t_{kj}: travel time from candidate stop $k \in N$ to candidate stop $j \in N$
c_{ik}: distance between demand point $i \in I$ and candidate stop $k \in N$
a_{lp}: maximum distance threshold to achieve coverage level $l \in L$ for group $p \in P$
T: maximum working time
e: number of nurses assigned to the mobile vaccination clinic
s_{max}: maximum service time
ε: a very small number

Decision Variables

$x_k = 1$, if candidate stop $k \in N$ is visited, and 0 otherwise
$y_{kj} = 1$, if candidate stop $j \in N$ is visited right after candidate stop $k \in N$, and 0 otherwise.
v_{ipkl}: number of vaccinated people of priority group $p \in P$ at demand point $i \in I$ by candidate stop $k \in K$ with service level $l \in L$
$z_{ipkl} = 1$, if people of priority group $p \in P$ at demand point $i \in I$ can be served by candidate stop $k \in K$ with service level $l \in L$
s_k: service time at candidate stop $k \in N$
u_k: auxiliary variable for sub-tour elimination constraint

The IP formulation is presented as follows.

$$\max \sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{k=0}^{N}\sum_{l=1}^{L} r_p \alpha_l v_{ipkl} - \epsilon\Big(\sum_{k=0}^{N} s_k + \sum_{k=0}^{N}\sum_{\substack{j=0\\ j\neq k}}^{N} t_{kj} y_{kj}\Big) \quad (1)$$

$$s.t. \sum_{\substack{j=0\\ j\neq k}}^{N} y_{kj} = x_k \qquad \forall k \in N \quad (2)$$

$$\sum_{\substack{j=0\\ j\neq k}}^{N} y_{jk} = x_k \qquad \forall k \in N \quad (3)$$

$$\sum_{j=1}^{N} y_{0j} = 1 \quad (4)$$

$$\sum_{k=1}^{N} y_{k0} = 1 \quad (5)$$

$$x_k \leq 1 \qquad \forall k \in N\backslash 0 \quad (6)$$

$$u_k - u_j + (N-1)y_{kj} \leq (N-2) \qquad \forall k \in N\backslash 0, j \in N\backslash 0, j \neq k \quad (7)$$

$$\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{l=1}^{L} v_{ipkl} \leq V x_k \qquad \forall k \in N \quad (8)$$

$$\sum_{k=1}^{N}\sum_{l=1}^{L} v_{ipkl} \leq d_{ip} \qquad \forall i \in I, p \in P \quad (9)$$

$$\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{k=0}^{N}\sum_{l=1}^{L} v_{ipkl} \leq V \quad (10)$$

$$v_{ipkl} \leq z_{ipkl} V \qquad \forall i \in I, p \in P, k \in N, l \in L \quad (11)$$

$$c_{ik} z_{ipkl} \leq a_{lp} \qquad \forall i \in I, p \in P, k \in N, l \in L \quad (12)$$

$$s_k \geq \frac{\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{l=1}^{L} v_{ipkl} b}{e} + w x_k \qquad \forall k \in N \quad (13)$$

$$s_0 = 0 \quad (14)$$

$$\sum_{k=1}^{N} s_k + \sum_{k=0}^{N}\sum_{\substack{j=0\\ j\neq k}}^{N} t_{kj} y_{kj} \leq T \quad (15)$$

$$v_{ipkl} \geq 0 \qquad \forall i \in I, p \in P, k \in N, l \in L \quad (16)$$

$$x_k \in \{0,1\} \qquad \forall k \in N \quad (17)$$

$$y_{kj} \in \{0,1\} \qquad \forall k \in N, j \in N \quad (18)$$

$$z_{ipkl} \in \{0,1\} \qquad \forall i \in I, p \in P, k \in N, l \in L \quad (19)$$

$$s_k \geq 0 \qquad \forall k \in N \quad (20)$$

The objective function (1) maximizes the weighed number of vaccinated people favoring higher service levels and more critical priority groups. Since the aim of this model is not to minimize the total distance or cost primarily, the total travel and service time is multiplied by a small number to eliminate alternative optima. Constraints (2) ensure that if arc y_{kj} is traversed, candidate location k is visited exactly once. Similarly, constraints (3) ensure if arc y_{jk} is traversed, candidate stop k is visited exactly once. Constraint (4) enforces the mobile vaccination clinic to leave the depot, whereas constraint (5) enforces it to return to the depot. Constraints (6) state that each candidate stop is visited at most once. Constraints (7) are sub-tour elimination constraints. Constraints (8) states that vaccination cannot occur at candidate stop k unless candidate stop k is visited. Constraint (9) guarantees that the total number of vaccines to be administered to a group cannot exceed its demand. Constraint (10) sets an upper bound for the maximum doses of vaccines to be administered. Constraints (11) ensure that a person cannot be vaccinated with service level l if candidate stop k is not in the maximum distance threshold. Constraints (12) determine whether candidate stop k can provide service level l to people from group p at demand point i. Constraints (13) calculate the total service time at each location, whereas constraint (14) ensures that the service time at the depot node is 0. Constraint (15) guarantees that the total travel and service time is within the working time limit. Constraints (16) -(20) define the decision variables.

4. Results and Discussion

In this section, first, the case study characteristics and parameters are introduced briefly, and then the outcome is discussed.

4.1 Case Study

To illustrate the implementation of the proposed model, a case study that considers a network based on the towns in Van province in Turkey is presented. Van is located in the Eastern part of Turkey and is considered the 4th most socioeconomically vulnerable province in Turkey according to TEPAV (2021). As of October 2021, 67.2% of the population of Van is fully vaccinated, which is about 11% less than the overall fully vaccinated population in Turkey (Turkey Ministry of Health 2021). This province was selected for the case study implementation due to the remoteness of the rural parts, as well as limited healthcare resources.

The data needed for the implementation of the model is adapted from Noyan et al. (2015). The available dataset contains 94 settlements (i.e., towns and villages) in Van, and relevant information about the network, such as population, demographics, location of settlements, and the travel times from each settlement to the others. The first settlement in the dataset is the central part of the city, however, since there are healthcare providers and infrastructure in this area, it is excluded from the set of demand points, instead, it is assumed that the depot is located in this first settlement (i.e., the central part of the city). Furthermore, it is assumed that the province is divided into three regions, each containing 31 settlements, and each will be served by one mobile vaccination clinic. Thus, the MVCRP is solved separately for each region.

The proposed model is general and can cope with varying service level requirements. However, since the focus of this case study is a province with rural settlements and due to lack of data, it is assumed that there is only one service level at each settlement and that all priority groups at all demand points are within the distance threshold for this service level. This assumption means that the demand point set is also considered as the candidate stop set for this setting.

From this dataset, 65+ population was assumed to be the first priority group due to their vulnerability towards Covid-19, the population of disabled people to be the second priority group due to the immobility issues they face, and the remaining eligible population who can receive vaccination (i.e., ages 15 and above) to be the third priority group. The demand of priority groups 1, 2, and 3 vary between 2 and 447, 0 and 609, and 67 and 9425 among settlements, respectively.

The maximum working time is set to 16 hours according to TRTHaber (2021). It is assumed that vaccines can be administered in 5 minutes per person, and the fixed setup and waiting time at stops is limited to 20 minutes. Another assumption is that capacity is not a restrictive factor in this setting. Extensive numerical results showing the effect of the number of nurses in the mobile vaccination clinic and varying priority weights were performed on this dataset, and the results are presented in section 4.2.

4.2 Results

In this section, the initial results are presented, which are obtained from an intel core i7 10th generation computer with the CPLEX 20.1.0.0 solver, and the model was coded using Java.

Sensitivity analysis is conducted on r_p (priority weight for group p) and e (number of nurses in the mobile clinic) parameters to observe the effects of these parameters on the results. Two different schemes for r_p parameter are considered:

- Prioritization Scheme 1 (PS1): All groups have equal priority weights ($r_1 = r_2 = r_3 = 0.33$)
- Prioritization Scheme 2 (PS2): The first group (P1) is prioritized over the second group (P2), and the second group is prioritized over the third (P3). ($r_1 = 0.7,\ r_2 = 0.2,\ r_3 = 0.1$)

These schemes are also tested with 2 ($e = 2$) and 5 ($e = 5$) nurses assigned to the mobile vaccination clinic.

The coverage percentages of each group and the overall network are measured, where the coverage percentage is defined as the ratio of the number of vaccinated people and the demand. The number of visited stops, total service time at stops, and the total route time are also reported to measure how effectively the limited time was spent. An example route of the vehicles for each region under the setting with two nurses ($e = 2$) and PS2 is illustrated in Figure 2. The metric values for all settings are presented in Table 1. The route in each cluster is represented with R1, R2, and R3 in the table for clusters 1, 2, and 3, respectively.

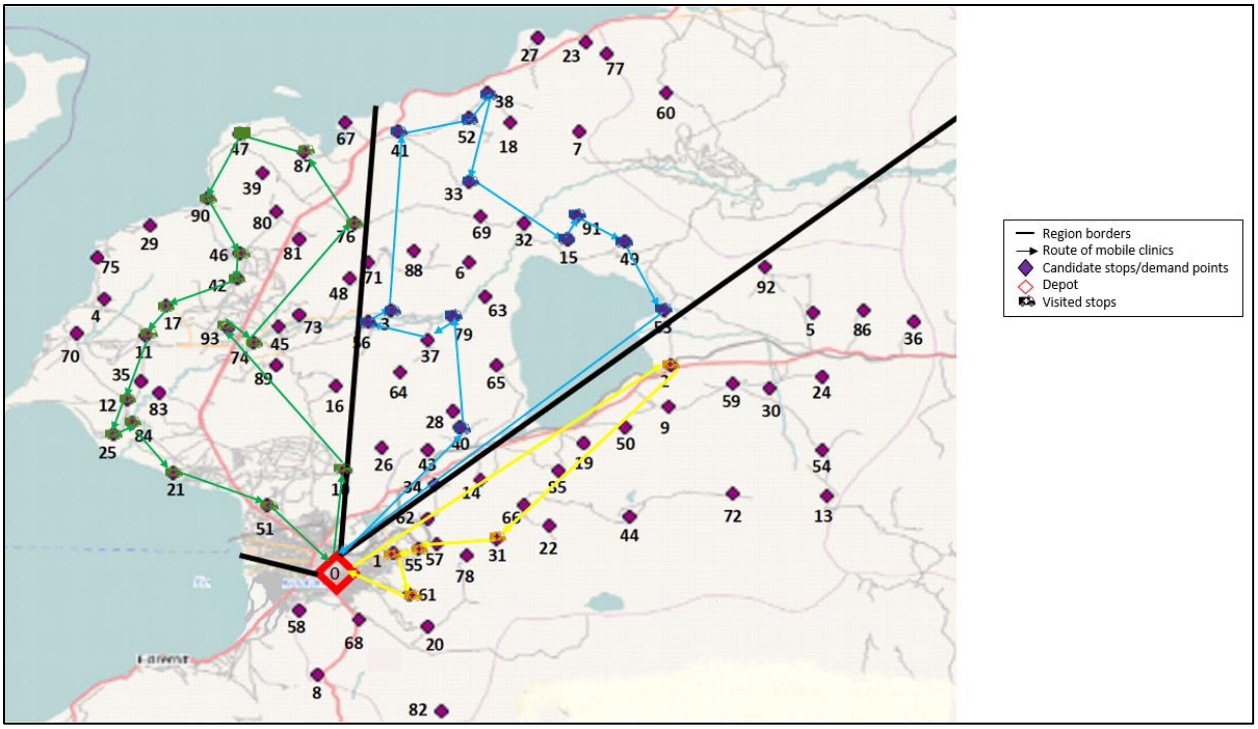

Figure 2: Representation of routes in the setting with e=2 and PS2 (The map is adapted from Noyan et al. (2015))

Table 1: Analysis of the results under different settings

	e = 2						*e*= 5					
	PS1			PS2			PS1			PS2		
	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
Total service time (in min)	925.0	905.0	937.5	802.5	727.5	932.5	925.0	827.0	938.0	742.0	707.0	842.0
Total route time (in min)	34.3	54.9	21.3	156.9	230.3	26.9	34.3	132.7	21.3	217.4	253.0	117.5
Visited settlements and routes	0-51-0	0-34-43-0	0-68-0	0-51-21-84-11-17-46-10-0	0-41-38-3-56-37-49-53-40-0	0-1-0	0-51-0	0-38-0	0-68-0	0-10-93-74-76-87-47-90-46-42-17-11-12-25-84-21-51-0	0-40-79-37-56-3-41-52-38-33-15-91-49-53-0	0-2-31-55-1-61-0
Coverage percentage of P1	0.0%	1.9%	0.0%	48.6%	55.0%	28.8%	0.0%	12.2%	0.0%	77.7%	69.3%	58.6%

Coverage percentage of P2	11.7%	3.6%	3.5%	0.3%	0.3%	0.0%	11.7%	13.2%	3.5%	0.0%	48.5%	0.0%
Coverage percentage of P3	2.7%	4.9%	1.4%	0.0%	0.0%	0.0%	7.3%	10.7%	3.7%	0.0%	0.0%	0.0%
Network-level coverage percentage	2.8%	4.7%	1.4%	2.1%	3.1%	1.4%	7.1%	10.9%	3.5%	3.3%	6.0%	2.8%

As shown in Table 1, employing more nurses has a direct effect on the total coverage levels. For instance, under PS2, it is observed that although the total service time is lower for the setting with 5 nurses than the setting with 2 nurses, the network-level coverage is still higher than the setting with two nurses.

Prioritization of groups (i.e., PS2) leads to higher percentage coverage percentages for P1 compared to the ones computed at PS1, where it significantly decreases the coverage percentages of P2 and P3. With a fewer number of nurses, the decrease in the coverage percentage of P2 is more drastic.

Moreover, it is found that as the priority weights among groups are differentiated, the network level coverage percentages decrease. That is due to the fact that the mobile vaccination clinics aim to increase the number of vaccinations for P1, and visit the P1 population in different settlements rather than increasing the time they spend in fewer stops and vaccinating less prioritized groups. The tradeoff caused by the prioritization of groups can be observed from the increased number of utilized stops, the larger route times, and the decreased service times. Using appropriate priority weights is crucial for this problem since it directly alters the effectiveness of the solution.

5. Conclusion and Future Directions

Implementation of Covid-19 vaccines has drastically lowered the infection rates, however, there are challenges on the administration of vaccines. One of the challenges is to vaccinate the population in remote areas, the immobile groups, and the groups that are vulnerable to the disease such as the elderly. In order to address this problem, An optimization-based solution is proposed that considers the different characteristics of location routing problems and the Covid-19 disease. An ILP model is developed to determine the daily routes of mobile vaccination clinics, as well as the service time at each stop, and the number of people to be vaccinated from each group. The preliminary results are presented including a sensitivity analysis on the parameters. The results indicate that there is a tradeoff to be considered between the prioritization of groups and the network-level effectiveness of the solution.

A possible future extension to the proposed solution is to consider a multi-period setting, where MVCRP is solved repeatedly until all demand groups are fully vaccinated. In that case, in order to prevent unnecessary trips between depot and settlements, logistics costs may become an important aspect. Another promising extension is to take the stochasticity of demand into account, and the possibility of no-shows to appointments.

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