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# A goal programming model for two-stage COVID19 test sampling centers location-allocation problem

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**Abstract**
The COVID19 virus, which first appeared in Wuhan, China, and has become a pandemic in a short time, has threatened the health system in many countries and put it into a bottleneck. Simultaneously, the second wave's expectation spread it necessary to plan the health services correctly. In this study, a location-allocation problem in the two-echelon system, which considers different test sampling alternatives, is examined to obtain test sampling centers' location-allocation. The problem is modeled as a goal programming model to create a network that tests samples at a minimum total distance, establishes a minimum number of test sampling centers, and reaches the distance of PCR test laboratories at minimum total distances. The proposed model is applied as a case study for the two cities located in Turkey, and the obtained locations and inventory levels of each location are presented. Besides, different scenarios are examined to understand the structure of the model. As a result, only testing in hospitals will increase the risk of contamination. Since testing at all points will not be possible administratively, it will be ensured that the most appropriate location-allocation decisions are taken by considering all the proposed model's objectives.

**Keywords** Location-allocation problem · Test sampling center location · Goal programming model · COVID19 pandemic

## 1 Introduction and literature review

There is unknown pneumonia in Wuhan; China is reported to the World Health Organization (WHO) Country Office in China on 31 December 2019, and this pneumonia is called COVID19 and is announced as a pandemic by WHO on March 2020. COVID19 spreads to 216 different countries with 4,258,666 confirmed cases and 294,190 deaths on 15 May 2020.

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According to statistics, it is seen that COVID19 is a very critical disease in terms of mortality rates and the rate of spread. One of the most important issues is to reduce the spread and provide the isolation of the virus by creating treatment and vaccine alternatives. Test methods and rapid testing are significant issues in reducing the spread. Testing applications may be corrupted or delayed during some problems such as taking more than 48 h to obtain test results, rapid increasing demand above capacity, fatigue, or infection of employees, and maintenance requirements of devices (World Health Organization 2020a, b).

Different COVID19 tests and their procedures are also presented by WHO (World Health Organization 2020a, b). The standard testing method of the diagnosis of the COVID19 is Polymerase Chain Reaction (PCR) tests. Furthermore, some other test methods can be called rapid test cards.

Rapidly diagnosing the COVID19 can decrease the spread of this virus. Xu and Li (2020) reported a new second wave of the COVID19 and the exponential increase in the pandemic threat the healthcare services' continuity. Awareness and preparedness will be more critical in the second wave; therefore, managing the pandemic process is crucial. To prevent the sharp increase in the number of cases, the importance of providing contact and isolation in all services has increased to provide control in the second wave. Countries' success in managing pandemics and providing services that will protect isolation are also essential factors that decrease the spread of cases. Harapan et al. (2020) summarize the current literature about the COVID19 with different perspectives, including managing the pandemic process.

In the literature on managing the pandemic process, the first important point is to determine the prediction of COVID19 spread. The spread evaluation of COVID19 in Spain is presented by the Monte-Carlo simulation approach (Baltas et al. 2020). The spread analysis of the first wave in China and the control methods are discussed (Leung et al. 2020). A gradient based prediction for COVID19 in US is proposed by Khalilpourazari et al. (2021). Sajadi et al. (2020) investigate the effects of parameters such as temperature and humidity on the potential spreading to COVID19. Kuvvetli et al. (2021) propose different artificial neural network and deep learning algorithms to predict the spread of COVID19 for different countries. Rest and Hirsch (2021) consider a home-healthcare scheduling problem during pandemic by proposing a decision support system. Besides, a discrete-event simulation model for evaluating the hospital preparedness during pandemic is proposed (Garcia-Vicuña et al. 2021).

In this study, a location-allocation model is proposed to eliminate the effects of test alternatives and their harmful effects on the spread of virus. With the increase of the test possibilities, where the tests will be carried has become essential. Sampling tests in a single-center have increased the risk of infection of patients who do not show symptoms and are caused by increased contact with the external environment to take the test. In this study, a mathematical model is proposed to determine the inventory quantities required for rapid diagnostic tests according to the location of test sampling centers and test sampling centers. This model consists of three layers as shown in Fig. 1: (1) geographic information layer, (2) test requirements layer, and (3) test sampling center location layer. A distribution is made according to the potential test and distance amounts with which center sampling centers should work.

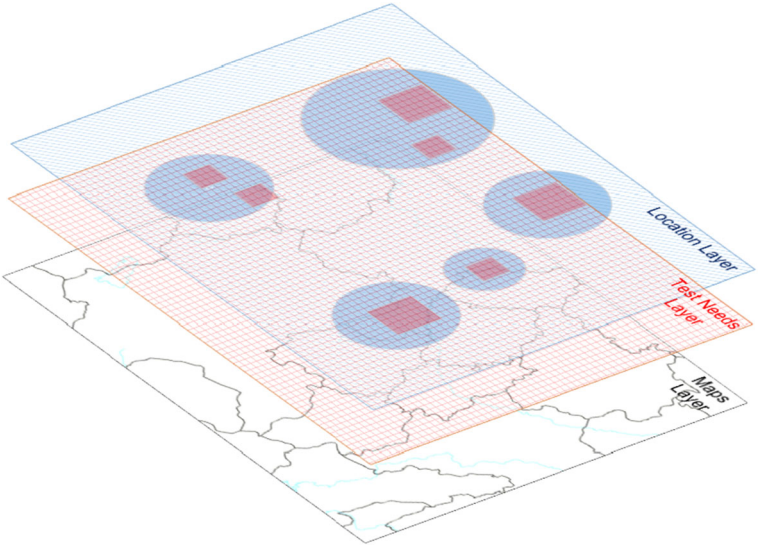



**Fig. 1** Problem structure

Location-allocation decisions have been studied in the literature with different applications in recent years. The structure of the problems has expanded to include different levels of supply chains (Fathollahi Fard and Hajaghaei-Keshteli 2018), containing settlement decisions with continuous location nodes (Lara et al. 2018), including geographic information-based systems (Lei et al. 2016), renewable energy systems infrastructure design (Kuvvetli 2020), and sustainability-oriented municipal solid waste location problems (Yu and Solvang 2017).

In the location-allocation problem, there are also studies for dangerous materials and disaster situations. In one of these, a mathematical model is proposed that considers the location of the facility, the selection of hazardous warehouses, distribution, and contingency plans (Fan et al. 2019). The location-allocation problem in the earthquake relief center location is studied to solve with genetic algorithm and bees algorithm (Saeidian et al. 2016). Another study considers the multi-level facility location problem for post-disaster statement (Shavarani 2019). A mathematical model is proposed for the selection of shelter locations in Syria (Hallak et al. 2019). Humanitarian disasters are studied with different studies such as Temporary Disaster Debris Management Site selection problem (Habib and Sarkar 2017) and a mathematical model for distribution center location and capacity optimization showing an earthquake preparedness (Paul and Wang 2019). Uncertainties of supply networks in disaster relief is introduced considering integration of forecasting and simulation methods (Meyer-Nieberg et al. 2014). Ambulance locations in crisis conditions are also determined by re-location decisions (Schneeberger et al. 2016).

Studies in which multi-objective versions of the location-allocation problem are discussed have been preferred in recent years. In one study, the location-allocation problem for grain silos has been studied as multi-purpose and multi-period (Mogale

et al. 2018). In another study that considers the problem's multi-objective type, health care center location-allocation decisions are incorporated together (Zhang et al. 2016). It is shown that accessibility, building costs, and reducing population outside the facilities are vital objectives in the location-allocation of healthcare centers (Zhang et al. 2016). Another healthcare application is about the preventive health care center location problem which only considers the location decisions in multi-objective manner (Dogan et al. 2020).

In health care systems, location-allocation problems attract the attention of researchers. The problem is modeled for the treatment and rehabilitation necessary for strokes or traumatic brain injuries to obtain a minimal-cost plan (Syam and Côté 2012). Geographic information system-based approach for the network analysis to optimize for location/allocation modeling (Walsh et al. 1997). Another study is also considered a geographic information systems-based approach finding sleep medicine services network locations (Watts et al. 2013). A multi-objective approach considers travel costs, inequity to accessing clinics, land-use, and land acquisition minimization is proposed for the facility location/allocations (Beheshtifar and Alimoahmmadi 2015). The capacitated maximal covering location problem is studied for the district of Malaysia (Shariff et al. 2012). The location problem gets important when emergency conditions are faced. According to this aim, a dynamic location model is proposed for achieving best coverage of the ambulances (Moeini et al. 2015). In COVID19 pandemic, location and routing problem is considered in terms of sustainability for the medical waste management problem (Tirkolaee et al. 2021).

The study considers the geographic information systems-based problem with multi-objective location-allocation problems with two-echelons covering test sampling centers and test centers as depicted in Fig. 2. The designated primary health care centers are selected as test sampling centers in the proposed test sampling network. It ensures that people are close to primary health care centers, where they can communicate quickly, and reduce COVID spread as it will reduce the occupancy of test centers. Performing test sampling in each primary health care center will be both costly and challenging to manage. However, since PCR tests can be performed according to the test results by performing rapid test sampling, rapid test operations are also performed in these centers. In the second echelon, an assignment is made to the PCR test laboratories for their PCR test needs following their capacities. Thus, the entire COVID19 test system is designed on the network. This study differs from the existing literature by considering a multi-objective perspective that focuses on all conditions with a minimum of operational costs, minimum of transportation risks, and a maximum of accessibility while covering both demand (neighborhoods) and supply (PCR test laboratories) areas by locating the intermediate points (which are test sampling centers). This approach provides a dynamic management tool for adjusting the test sampling centers regarding the transmission of the pandemic.

## 2 Methodology

According to the study's methodology summarized in Fig. 3, the first step is about obtaining the data. The data to be used in the problem can be considered in three groups:

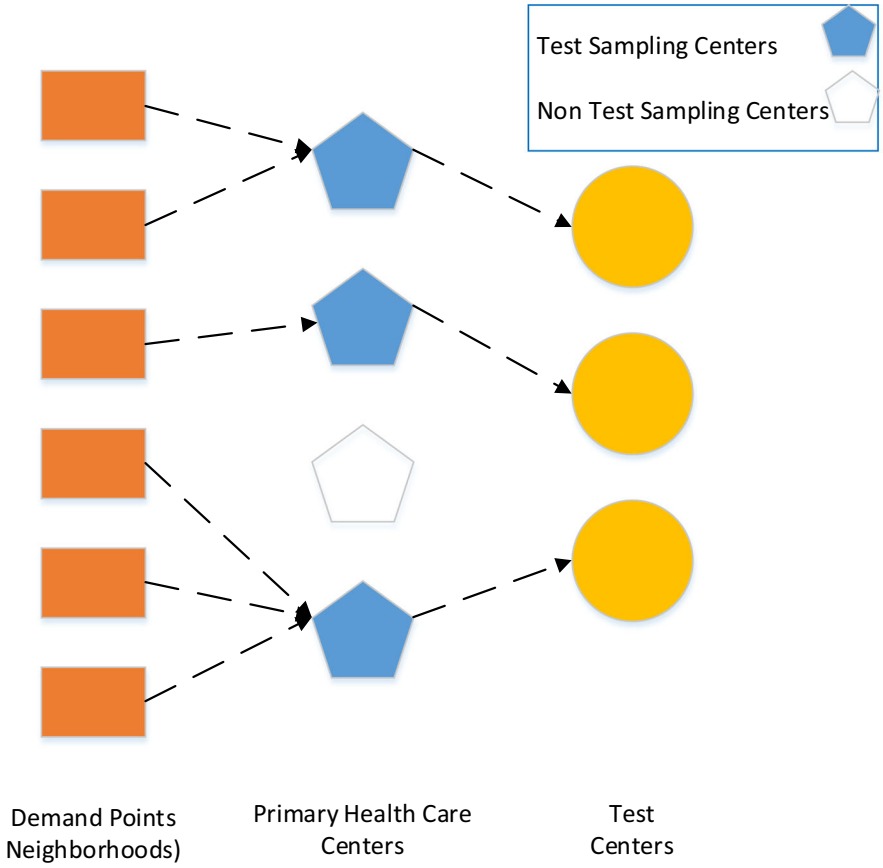



**Fig. 2** Proposed Location-Allocation Problem Description

the first of these is to obtain geographic locations and distance between neighborhoods and primary healthcare centers. The second group of data is the data of capacity and test centers related information. In the third group, some policies can change according to different conditions, such as targeted coverage, and they should be analyzed as scenarios. In this study, three different goals have been defined. The first aim is to establish the facility layout at a minimum distance. It aims to appoint candidate primary health care centers as test sampling centers with minimum distance for people in all neighborhoods. As a second goal, the minimum number of test sampling centers is considered. The third aim is to select test sampling centers with closeness to PCR test centers. Each of these single objective mathematical models is created separately regarding their objectives. A goal programming model, in which all the objectives are considered together, is created in the next step. In goal programming, each goal has a target value set by decision maker(s) and an achieved value from the model and both values are numeric (Jones and Tamiz 2010). In this study, target values are obtained

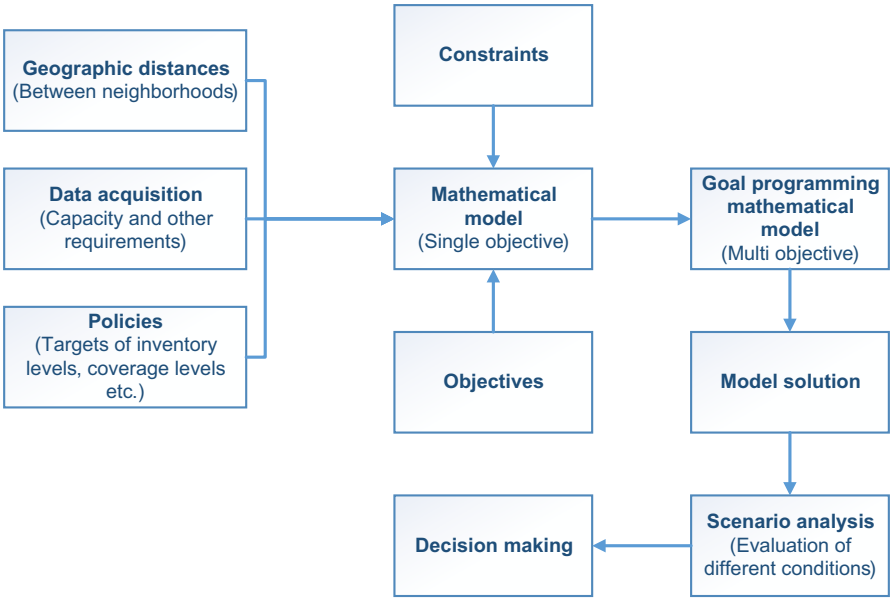



**Fig. 3** The methodology of the study

from single objective models. Finally, the models are solved, and scenario analyses are made for different policy situations to make the best decision.

Some conditions are assumed in the modeling of the system as given follows: (1) All the model parameters are known. (2) Each neighborhood should be covered only as a test sampling center. (3) All of the single objective models have the same weights as the goal programming model. (4) Capacity levels of PCR test laboratories are known in advance.

In this model, there are $I$ neighborhoods, $K$ primary healthcare center locations and $J$ PCR test laboratories. Each neighborhood has a population $p_i (i = 1, ..., I)$. $d_{ik}$ $(i = 1, ..., I; k = 1, ..., K)$ shows the distance between one neighborhood center and one primary health care center. Similarly, $b_{kj} (k = 1, ..., K; j = 1, ..., J)$ is the distance between one primary health care center and one of the PCR test laboratories. There are two types of tests which are PCR test and rapid test kits. The model considers the capacity of PCR test laboratories $Q_j$ $(j = 1, ..., J)$ along with the upper and lower bound of inventory levels for rapid test kits $u_k$ and $l_k (k = 1, ..., K)$. A test sampling center can only cover a limited area which is denoted by $T$; likewise, PCR laboratories can also serve a limited area which is denoted by $C$. A pandemic like COVID19 has a fast transmission rate $(\beta)$ in population which changes dynamically during pandemic process.

The problem includes three single objective functions which are (i) the maximum availability of test sampling centers model, (ii) the minimum number of test sampling centers model, and (iii) minimum distance to PCR laboratories model. Each single objective's optimal value is denoted by $z_1$, $z_2$, and $z_3$, respectively.

The decision variables of the mathematical model are given below:

| **Decision Variables** | |
|---|---|
| $x_{ik}$: | $\begin{cases}1, & \text{if a test sampling center located at } k \text{ serves to } i\\ 0, & \text{otherwise}\end{cases}$ |
| $y_k$: | $\begin{cases}1, & \text{if a test sampling center is located at } k\\ 0, & \text{otherwise}\end{cases}$ |
| $a_k$: | The need for rapid test kit inventory at the test sampling center $k$ |
| $w_{kj}$: | $\begin{cases}1, & \text{if the test sampling center } k \text{ is connected with the laboratory } j\\ 0, & \text{otherwise}\end{cases}$ |
| $s_1^+$: | Positive deviation from the first objective $z_1$ |
| $s_1^-$: | Negative deviation from the first objective $z_1$ |
| $s_2^+$: | Positive deviation from the second objective $z_2$ |
| $s_2^-$: | Negative deviation from the second objective $z_2$ |
| $s_3^+$: | Positive deviation from the third objective $z_3$ |
| $s_3^-$: | Negative deviation from the third objective $z_3$ |

In this mathematical modeling, three single objectives can be used, which are minimization of the total distance (1), minimization of the total number of test sampling centers (2), and minimum distances to PCR test laboratories (3). The goal programming objective function that handles all of these objectives together is given in (4).

$$minz_1 = \sum_{i\in I}\sum_{k\in K} d_{ik}\cdot x_{ik} \tag{1}$$

$$minz_2 = \sum_{k\in K} y_k \tag{2}$$

$$minz_3 = \sum_{j\in J}\sum_{k\in K} b_{kj}\cdot w_{kj} \tag{3}$$

$$minz = \frac{s_1^+}{z_1} + \frac{s_2^+}{z_2} + \frac{s_3^+}{z_3} \tag{4}$$

In the first objective function (1), the maximum accessibility is aimed to locate test sampling centers at minimum distances to the neighborhoods. The second objective function deals with building fewer test sampling centers to make a cost-efficient plan. Therefore, objective function (2) aims to minimize the total number of test sampling centers. The third objective function (3) provides a location plan that locates a test sampling center nearly PCR test laboratories to minimize samples' transportation. Finally, the last objective function (4) is the goal programming objective that considers all of these three objective functions together by minimizing each objective's relative deviations. The constraints of all of the mathematical models are given in Eqs. (5)–(24) as follows:

$$\sum_{i\in I}\sum_{k\in K} d_{ik}\cdot x_{ik} - z_1 = s_1^+ - s_1^- \tag{5}$$

$$\sum_{k\in K} y_k - z_2 = s_2^+ - s_2^- \tag{6}$$

$$\sum_{j\in J}\sum_{k\in K} b_{kj}\cdot w_{kj} - z_3 = s_3^+ - s_3^- \tag{7}$$

$$s_1^+ \cdot s_1^- = 0 \tag{8}$$

$$s_2^+ \cdot s_2^- = 0 \tag{9}$$

$$s_3^+ \cdot s_3^- = 0 \tag{10}$$

$$d_{ik}\cdot x_{ik} \le T\cdot y_k, \quad \forall_{i,k} \tag{11}$$

$$\sum_{i\in I} x_{ik} = 1, \forall_k \tag{12}$$

$$x_{ik} \le y_k, \forall_{i,k} \tag{13}$$

$$l_k \le a_k + M\cdot(1-y_k), \forall_k \tag{14}$$

$$a_k \le u_k \cdot y_k, \forall_k \tag{15}$$

$$a_k \ge \sum_{i\in I} x_{ik}\cdot p_i \cdot \beta, \forall_k \tag{16}$$

$$b_{kj}\cdot w_{kj} \le C, \forall_{k,j} \tag{17}$$

$$\sum_{k\in K} a_k \cdot w_{kj} \le Q_j, \forall_j \tag{18}$$

$$\sum_{j\in J} w_{kj} = y_k, \forall_k \tag{19}$$

$$x_{ik} \in \{0,1\}, \forall_{i,k} \tag{20}$$

$$y_k \in \{0,1\}, \forall_k \tag{21}$$

$$w_{kj} \in \{0,1\}, \forall_{k,j} \tag{22}$$

$$a_k \ge 0, \forall_k \tag{23}$$

$$s_1^+ \geq 0\ s_1^- \geq 0\ s_2^+ \geq 0\ s_2^- \geq 0\ s_3^+ \geq 0\ s_3^- \geq 0 \tag{24}$$

Constraint (5) ensures positive and negative deviations from the first objective function's optimal value. Similarly, Constraints (6) and (7) ensure that for the second and third objectives. The constraints (8)–(10) provide the only positive or negative deviations that can be permitted for the three objective deviations. Note that the Constraints (5)–(10) are valid only for the goal programming models; they are not included in single objective models.

Constraint (11) ensures that the distance between the located test sampling center and the neighborhoods it can serve should be within the allowable limit. Constraint (12) enables each neighborhood to receive service from one sampling test sampling center. Constraint (13) indicates that a test sampling center must have been built to serve. Constraints (14), (15), and (16) are related to the rapid test kit inventory of each test sampling center. Constraint (14) ensures the lower bound of the test center rapid test kit inventory, while Constraint (15) is the upper bound of the rapid test kit inventory. Constraint (16) ensures that a test sampling center should keep a rapid test kit inventory for the covered population. Constraints (17)–(19) are the PCR test laboratory and test sampling center allocation constraints. Constraint (17) forces to assign test sampling center to a PCR test laboratory with less than allowed distances between them, while Constraint (18) provides to avoid excessing test capacity of the PCR test laboratory. Constraint (19) ensures that each test sampling center should be assigned a PCR test laboratory. Constraints (20)–(24) refer to the valid ranges of variables.

## 3 Results

In this section, the case study details are given in Sect. 3.1. The results obtained from the case studies are summarized in Sect. 3.2. Finally, the sensitivity analysis that considers the tendency of the model in Sect. 3.3.

### 3.1 Case study

In the case of the study, according to the Turkish Minister of Health, there are two main types of tests applied which are PCR tests and rapid test kits. The case study consists of two major cities of Turkey are Istanbul and Adana. Istanbul is a very historical place that is the capital of three empires and Turkey's most crowded city (Governorship of Istanbul 2020). 15,067,724 people live in Istanbul in 5712 $km^2$ area with 39 districts (Istanbul). The study area from Google Maps is depicted in Fig. 4. Due to the Bosphorus, the city is divided into two different sides, which are European and Anatolian sides. Therefore, three cases which are Adana, Istanbul European, and Anatolian sides, are conducted.

Adana is the sixth crowded city of Turkey, which is located in the southern part of Turkey. Adana has a population of about 2.3 million and has a coastline in some districts. Adana has 15 districts, and four of them are the central districts of the city. The Google Maps figure of the study area of Adana is shown in Fig. 5.

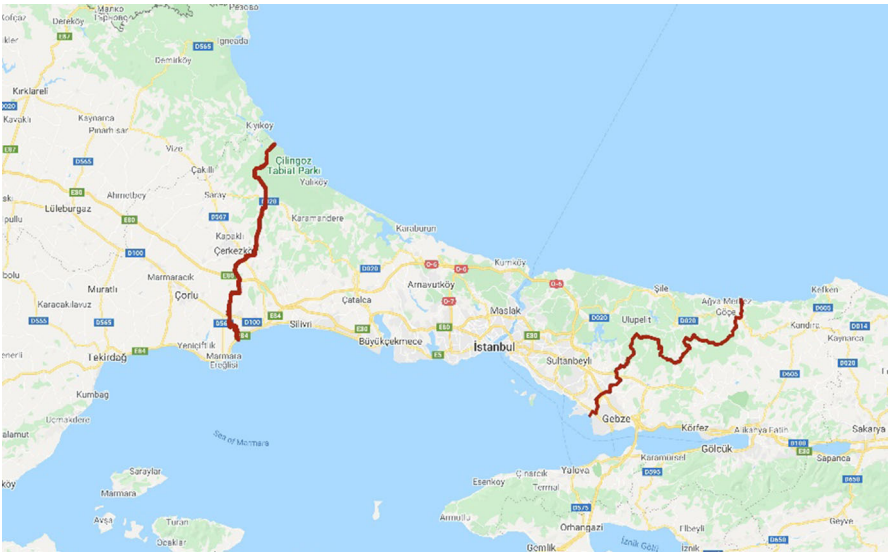



**Fig. 4** The study area of Istanbul




**Fig. 5** The study area of Adana

**Table 1** Description of parameter values

| Parameters (Notations) | Istanbul | | Adana |
|---|---|---|---|
| | European side | Anatolian side | |
| Number of neighborhoods ($I$) | 595 | 359 | 299 |
| Number of primary health care centers ($K$) | 633 | 370 | 299 |
| Number of PCR test laboratories ($J$) | 10 | 6 | 2 |
| Minimum populated neighborhood ($min_i\{p_i\}$) | 14 | 58 | 20 |
| Mean populated neighborhood ($\overline{p}$) | 16,347 | 14,730 | 5,916 |
| Maximum populated neighborhood ($max_i\{p_i\}$) | 93,229 | 82,651 | 64,929 |
| Minimum distances between neighborhoods ($min_{i,k}\{d_{ik}\}$) | 0 km | 0.02 km | 0 km |
| Mean distances between neighborhoods ($\overline{d}$) | 21.22 km | 19.8 km | 26.84 km |
| Maximum distances between neighborhoods ($max_{i,k}\{d_{ik}\}$) | 123.65 km | 92.56 km | 91.59 km |
| Minimum distances between neighborhoods and candidate test sampling centers ($min_{k,j}\{b_{kj}\}$) | 0.2 km | 0.2 km | 0 km |
| Mean distances between neighborhoods and candidate test sampling centers ($\overline{b}$) | 14.62 km | 12.8 km | 18.01 km |
| Maximum distances between neighborhoods and candidate test sampling centers ($max_{k,j}\{b_{kj}\}$) | 83.3 km | 65.64 km | 52.02 km |

Both Adana and Istanbul are crowded cities of Turkey. Therefore, the spread of COVID19 is vital for these cities. The population data of the model is obtained from the Turkish Statistical Institute. The distances between neighborhoods, test sampling candidates and PCR test laboratories are obtained from Google Maps. All of these problem parameters are summarized in Table 1. Other problem parameters are summarized in Table 2. Inventory levels are calculated from populations of neighborhoods and transmission probability values. Coverage targets are also calculated from the distance parameters as a percent of distances. Transmission probability may change during the pandemic.

### 3.2 Results

All created models were solved using GAMS software and SCIP solver in a PC with a 3.6 GHz dual-core processor and 16 GB of RAM. The solution time of all models is $<$ 6 h. The proposed goal programming model results are summarized in Table 3 for all

**Table 2** Adjustable parameters of the models

| Parameters | Istanbul | | Adana |
|---|---|---|---|
| | European side | Anatolian side | |
| Transmission probability ($\beta$) | 0.001 | 0.001 | 0.001 |
| The maximum coverage area of the test sampling center ($T$) | 46 km | 32.3 km | 32.05 |
| Rapid test kit inventory lower bound ($l_k$) | 1 | 1 | 1 |
| Rapid test kit inventory upper bound ($u_k$) | 466 | 165 | 324 |
| The maximum coverage area of PCR test laboratories ($C$) | 67.33 km | 49.3 km | 44.2 km |
| The minimum capacity of PCR test laboratories ($min_j\{Q_j\}$) | 500 | 500 | 460 |
| The mean capacity of PCR test laboratories ($\overline{Q}$) | 1350 | 1583 | 1000 |
| The maximum capacity of PCR test laboratories ($max_j\{Q_j\}$) | 6000 | 6000 | 1540 |

three case studies. Firstly, it is observed that the highest deviation for the three purposes occurred for the Istanbul European side case model. The lowest deviation from all three objectives obtained from the Istanbul Anatolian side case model. Differences in deviations varied due to the neighborhoods' distance to test sampling centers and distance from test sampling centers to PCR test centers. Considering the range values and average values of all distances, the high deviations in the Istanbul European and Adana case models can be explained.

When the aim of closeness to neighborhoods, which is the first objective, is examined, the total distance of 642.93 km for the European side of Istanbul, 1,016.55 km for the Anatolian side and, 21.91 km for Adana are located. Accordingly, it is seen that the distance and number of neighborhoods affected the first goal.

For the second objective, the minimum number of test sampling centers, a test sampling center, has been determined as 31 on the European side of Istanbul, 33 on the Anatolian side, and 4 on Adana. When the inventory amounts are examined, the highest inventory level was used in the Istanbul European case model. For this reason, the essential parameters on the number of test sampling centers opened are inventory amounts, target coverage area, and distance between neighborhoods.

When the third objective that considers closeness to PCR test laboratories, is examined, it is seen that the highest total distances are on the European side of Istanbul, the next highest total distances are on the Anatolian side of Istanbul, and finally, the lowest total distances are in Adana. Here, the relationship of the targeted maximum coverage area value with distances emerges as an essential parameter.

When a general evaluation is made for the three cases, it is seen that the Istanbul European side model focuses on giving results in a smaller number of test centers.

**Table 3** Summary of case study results

| Performance Criteria | Istanbul | | Adana |
|---|---|---|---|
| | European Side | Anatolian Side | |
| The objective value of maximum availability of test sampling centers model ($z_1$) | 642.93 | 1016.55 | 21.91 |
| The objective value of the minimum number of test sampling centers model ($z_2$) | 31 | 33 | 4 |
| The objective value of minimum distance to PCR laboratories model ($z_3$) | 862.87 | 507.51 | 40.76 |
| The objective value of the goal programming model ($z$) | 23.49 | 0.75 | 65.8931 |
| Number of test sampling centers ($\sum_{k \in K} y_k$) | 31 | 42 | 37 |
| Minimum distances to test sampling centers ($min_{i,k}\{d_{ik} \cdot x_{ik}\}$) | 0.05 km | 0.02 km | 0 km |
| Mean distances to test sampling centers ($\overline{d \cdot x}$) | 26.4 km | 4.19 km | 3.44 km |
| Maximum distances to test sampling centers ($max_{i,k}\{d_{ik} \cdot x_{ik}\}$) | 46.22 km | 25.96 km | 51.97 km |
| Minimum inventory levels ($min_k\{a_k\}$) | 1 | 13 | 1 |
| Mean inventory levels ($\overline{a}$) | 313 | 126 | 48 |
| Maximum inventory levels ($max_k\{a_k\}$) | 466 | 165 | 264 |
| Minimum distances to PCR test laboratories ($min_{k,j}\{b_{kj} \cdot w_{kj}\}$) | 14.48 km | 0.71 km | 0 km |
| Mean distances to PCR test laboratories ($\overline{b \cdot w}$) | 27.83 km | 11.76 km | 2.36 km |
| Maximum distances to PCR test laboratories ($max_{k,j}\{b_{kj} \cdot w_{kj}\}$) | 66.88 km | 48.58 km | 37.71 km |

It is because it is the region with the highest distance to both PCR test centers and neighborhoods. It allowed the model to tend to open less test sampling centers as the distances increased. Another point is that the model can be affected by different bottlenecks while creating an optimal plan. When evaluating Istanbul case models, the inventory amounts are at the upper limit level, indicating that a new location has been opened due to inventory rather than distances. For Adana, especially less test sampling center is selected due to the less distance between neighborhoods as given in Table 1. Figures 6 and 7 show the settlements obtained for Istanbul and Adana. An intensive settlement plan has been created in regions with high population density.

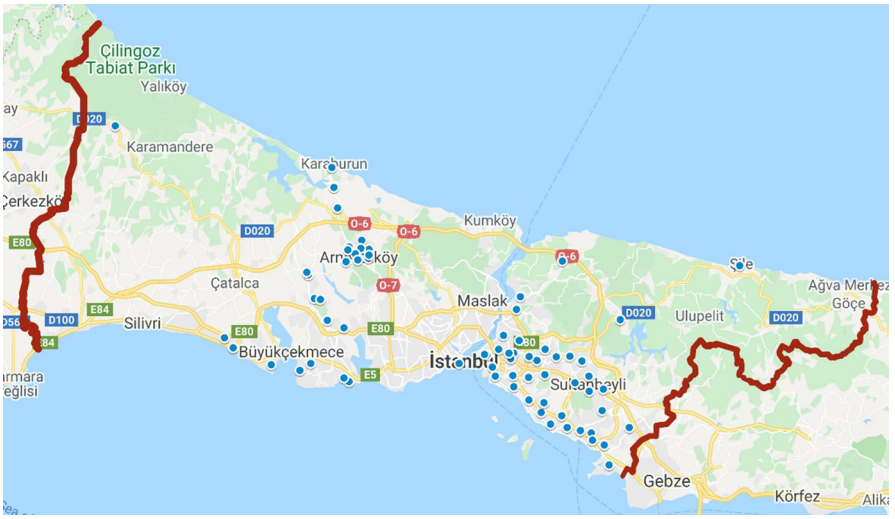
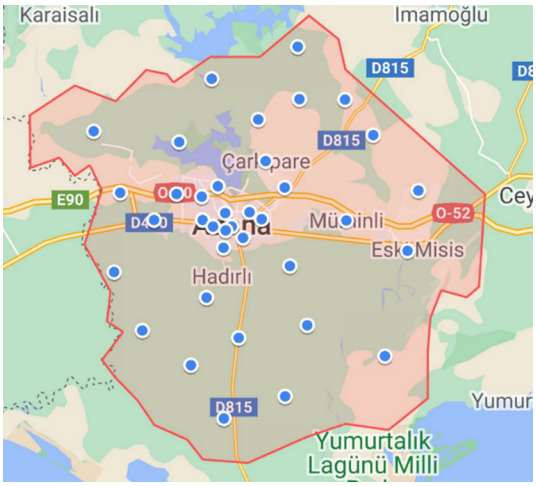



**Fig. 6** Results of Istanbul case

**Fig. 7** Results of Adana case




### 3.3 Sensitivity analysis

When the case study results are presented in the previous section, it is observed that different parameter values produced different results on the solution of the models. For this reason, these results were reevaluated for the case of different parameters similar to the Adana sample. For this purpose, the model has been resolved for different values of targeted coverage area between neighborhoods and test sampling points, test sampling points, and targeted coverage area between PCR test centers and different infection rates. $\pm$ 20% is taken as the change interval of the parameters.

The results obtained for the targeted coverage area of test sampling centers parameter ($T$) are presented in Table 4. Accordingly, there has been no change in the primary intention of minimum proximity. It is acceptable for this distance minimization objective. It is seen that the results changed in the number of test sampling centers opened and distance to PCR test laboratories. Similarly, goal programming model results have changed, and as $T$ increases, deviation from three objectives has also increased. When the number of test centers opened is analyzed, the number of test sampling centers opened has decreased as $T$ is increasing since it can serve on a broader area. When the distances are examined, the average distance values decreased as $T$ increases since more services can be obtained on a broader area. Similar conclusions are obtained from the closeness of PCR test centers. Finally, there is no significant change in the rapid test kit inventory level.

According to the changes in the targeted coverage area of PCR laboratories ($C$) which is summarized in Table 5, it is observed that the model was infeasible at values below the target value. It is because the targeted value is very close to the minimum distance value. As the $C$ value increases, the aim of establishing a test sampling center with a minimum distance decreases. It can be explained by installing test sampling centers in more distant locations. For this reason, deviation values from all objectives increased in the goal programming results. As $C$ increases, more test sampling centers will be opened closer, and more test sampling centers will be installed.

Another critical parameter is the transmission rate ($\beta$). Although this ratio is a parameter used in calculating many parameters, it did not significantly affect the results. The reason for this is that the 20 percent change in $\beta$ did not have a good effect on inventory levels and other decision variables. Therefore, it is concluded that the model is robust to changes in the infection rate.

**Table 4** Sensitivity analysis results for the targeted coverage area of test sampling centers

| The targeted coverage area of test sampling centers | First Objective | Second Objective | Third Objective | Goal Programming Objective | Number of test sampling centers | Mean distances to test sampling centers | Mean distances to PCR test laboratories | Mean inventory levels |
|---|---|---|---|---|---|---|---|---|
| (−)20% | 21.91 | 42 | 977.91 | 9.49 | 271 | 0.11 | 16.57 | 7.02 |
| (−)10% | 21.91 | 38 | 891.05 | 10.61 | 263 | 0.12 | 16.92 | 6.73 |
| Current Value | 21.91 | 31 | 727.09 | 13.20 | 247 | 0.18 | 17.11 | 7.70 |
| (+)10% | 21.91 | 26 | 624.43 | 15.65 | 236 | 0.22 | 17.47 | 7.5 |
| (+)20% | 21.91 | 22 | 509.08 | 18.69 | 218 | 0.30 | 17.92 | 8.11 |

**Table 5** Sensitivity analysis results for the targeted coverage area of PCR test laboratories

| The targeted coverage area of PCR test laboratories | First Objective | Second Objective | Third Objective | Goal Programming Objective | Number of test sampling centers | Mean distances to test sampling centers | Mean distances to PCR test laboratories | Mean inventory levels |
|---|---|---|---|---|---|---|---|---|
| (−)20% | ~ | ~ | ~ | ~ | ~ | ~ | ~ | ~ |
| (−)10% | ~ | ~ | ~ | ~ | ~ | ~ | ~ | ~ |
| Current Value | 21.91 | 31 | 727.09 | 13.20 | 247 | 0.18 | 17.11 | 7.70 |
| (+)10% | 5.91 | 31 | 727.09 | 14.03 | 291 | 0.02 | 16.54 | 6.08 |
| (+)20% | 0.00 | 31 | 727.09 | 15.22 | 294 | 0.00 | 16.65 | 6.02 |

## 4 Conclusion

Despite its emergence in China in December 2019, the COVID19 pandemic, which affected the whole world quickly, affects the whole world from different perspectives. In terms of public health, management of the pandemic, preventing its spread, and keeping the health system working are critical issues. In this context, in this study, test sampling centers' location-allocation decisions to be used in obtaining test samples for COVID19 are discussed in a two-stage structure. In this structure, three significant aims should be handled. Closeness to the neighborhoods where the community lives seem a manageable system with a minimum number of sampling centers; conversely, closeness to laboratories where PCR tests will be carried out eliminates delays and problems during the transportation of samples. In this study, a goal programming model, which takes all these goals together, is proposed. The proposed model results create the location-allocation maps for both cities. Accordingly, it was observed that the model was not affected by the 20% change in the transmission rate.

In such a pandemic, test sampling is one of the key factors in the transmission of the disease. Another important factor is decreasing the mobility of the people to avoid touch with possible patients. Therefore, it is important to make PCR or other COVID19 detection tests closer to the population and giving a rapid response of the tests to them. The model proposed in this study gives an insight for the decision makers to achieve an efficient test infrastructure regarding the transmission. Primary health care centers are considered as a candidate test sampling centers which is suitable not only a testing but also a logistic network of the health care system. Using the model outputs, some primary health centers will be test centers and, according to the progress of the pandemic, test centers can be updated by resolving the model. Thus, more successful pandemic management will be possible in terms of both accessibility, cost, and effective use of resources. In addition, since the amount of inventory to be used in each center will be determined, the possibility of the test needs to be backordered will be prevented, while inventory management will be done rationally.

This study's limitation is that due to the mathematical modeling approach, successful results can be obtained by knowing the parameters and predicting them accurately. Besides, all objectives have equal weights. For this reason, the goals can be weighted in future studies. Some assumptions are made in this study; for instance, covering each neighborhood at once may be considered secondary coverage permissions. It can be changed for administrative purposes such as these coverages. Finally, a decision support system can be created with map integration. The proposed method finds a solution in less than six hours; therefore, fast heuristic methods can be proposed for this problem.

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