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Logistics of Temporary Testing Centers for Coronavirus Disease

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Abstract

The ongoing COVID-19 pandemic has caused the death of millions of people, and PCR testing is widely used as the gold standard method to detect the infections to restrict the outbreak. Through the interviews conducted with people from the field in South Korea, the UK, and Turkey, we have found that there are numerous testing strategies worldwide. Those testing strategies include drive-through and home delivery testing capabilities, local test sites, and mobile test centers. Our primary motivation is to propose a generic model based on the best practices in the UK and South Korea. Also, we aim to present a case study on Turkey for the implementation of vital procedures and increase their availability.

This paper represents a study on how to construct a temporary testing logistics system during the initial phases of pandemics to increase the availability of PCR testing with the primary objective of maximizing total sample collection. The design also considers minimizing the maximum walking distance to increase the convenience of sample collection for the people living in the neighborhoods. The proposed system consists of temporary testing centers and a central laboratory. Temporary testing centers perform direct tours to the potential areas to collect samples and bring the collected sample to the designated central laboratories located at central hospitals. Moreover, to represent the non-linear inheritance of the pandemic progress within a population, we consider diminishing sample potentials over time and coverage. This new problem is defined as an extension of the Selective Vehicle Routing Problem and Covering Tour Problem.

We propose a mathematical model and four two-stage math-heuristic algorithms to determine the location and routing of the temporary testing centers and their lengths of stay at each visited location. The performances of the proposed solution methodologies are tested on two data sets. The first set is constructed by the confirmed cases of the districts of Seoul, Korea, and by the interview of health personnel of H+ Yangji Hospital COVID-19 semi-mobile booth application, and the second set is constructed by 99 hospital/health centers from distinct neighborhoods of 22 districts of Istanbul, Turkey. The Pareto set of optimum solutions is generated based on total sample collection and maximum walking distance. Finally, sensitivity analyses on some design parameters are conducted.

Keywords: Logistics, Routing, COVID-19 testing

1. Introduction

The current COVID-19 pandemic is a pandemic of the disease provoked by SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2). The first case of COVID-19 emerged in Wuhan, China, in December 2019. The spread of the virus was recognized as a pandemic on 11 March 2020 by the World Health Organization. At present, there are 630.6 million confirmed cases and 6.5 million deaths in total associated with COVID-19 worldwide (Johns Hopkins Coronavirus Resource Center, 2022).

There are various methods to detect infections in an attempt to restrict the COVID-19 outbreak. Antibody testing can be used for diagnosing past infections. Antigen and viral tests are utilized to identify

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ongoing infections; the former is convenient and fast but is not sensitive compared to the latter. The gold standard test to confirm the infection is polymerase chain reaction (PCR) testing.

The high contagion of the virus has caused the outbreak to become a global issue. The time interval during which an infected person may spread the virus is 1 to 14 days. As it takes time to obtain the results from viral tests, a potentially sick person is at risk of infecting others in that time interval. To prevent the virus from spreading, early detection of the infection is crucial for two main reasons. First, early detection of positive cases prevents the virus from spreading, as the infected are isolated from public areas, isolation dramatically affects the incidence of the disease. Second, early recognition of coronavirus-positive patients, especially those in the high-risk group or already ill with a critical condition, decreases mortality rate by monitoring and treating the patients in the early stages of the disease (Sun et al., 2020).

Due to the need for early recognition of the disease and to increase the reach of testing, numerous testing strategies have been utilized in different countries. We have interviewed people from countries including the UK, South Korea, and Turkey to understand the testing strategies used during the pandemic. The UK and South Korea are chosen for the interviews in order to understand the testing strategies extensively since they are the pioneer countries in implementing many testing strategies. We have learned that the drive-through and home delivery testing capabilities, local test sites, and temporary test centers are currently the most utilized testing strategies. The testing strategies can vary from country to country due to their circumstances, but any country can adopt a well-designed generic model. Even though some testing strategies exist in Turkey, the mobile testing application is not implemented. In this study, we propose a generic and easy-to-implement temporary testing logistics system based on the best practices in the UK and South Korea. The generic model is tested through a case study in Turkey.

The UK is one of the countries that enhance testing outreach through different strategies; including temporary testing centers. The government provided operational plans involving large drive-through testing capabilities and home delivery capabilities of testing kits. Drive-through testing is an application where patients arrive and are given the testing kits and the relevant instructions. In this way, the patients are virally tested without any direct human interaction. Home delivery testing is an application in which the subjects can order test kits via ordering portals. However, there are two problems regarding viral testing involving the patients themselves rather than health personnel. Firstly, strictly following the instructions is crucial for an accurate diagnosis. The improper collection of the samples leads to false-negative viral test results (Hu and Wang, 2020). Secondly, drive-through and home delivery capabilities provide access to viral testing to only a part of the community: English speakers and car owners. Due to the limited accessibility and availability of these testing strategies, a large proportion of the community living in high-density urban centers and areas with higher transmission rates may be excluded. The inclusion of health personnel is essential in the testing strategies in order to reach the community members who cannot be taught the viral testing instructions. Therefore, improper sample collection is eliminated.

Besides drive-through and home delivery, there are local test sites (walk-through sites) in common areas such as campuses, churches, and parking lots. The walk-through sites are intended to increase the availability of testing by reaching disadvantaged regions. All testing applications serve to provide intuition testing and search testing. The former is frequently used to test the disadvantaged part of the community to protect them, such as the elderly; the latter is used for testing as many people as possible in case of a particular outbreak. Furthermore, there is another testing strategy known as temporary test units to serve vulnerable parts of the community. They are mobile testing strategies based on the regional test sites, which are drive-through test sites. Temporary test units essentially operate on daily basis by dispatching from the regional sites with the test kits and return to the regional sites with the collected samples. Although these applications collect samples for viral testing, they cannot give the results of the tests. Therefore, laboratories with the obligatory biosafety levels conduct the PCR testing of the samples collected in the mobile facilities.

Similar operational plans have also been considered in South Korea, where the drive-through facilities had emerged earlier, with South Korea being the first country to implement this application. In addition, temporary screening centers play a vital role in testing; these are sophisticated mobile facilities that prevent direct human interaction due to the design of the facilities and the types of equipment that health personnel wear. This study is inspired by the advanced mobile testing example H+ Yangji Hospital Walk-Thru testing application in Gwanak-gu, South Korea. Currently, 95% of the samples are collected in temporary screening centers and drive-through applications under the Centers for Disease Control and Prevention supervision. Therefore, mobile facilities have a significant role in fighting the pandemic.

Currently, there are no mobile testing applications in Turkey, but it is advised that the temporary testing vehicles could help significantly if they are involved in the contact tracing process. The contact tracing teams test and keep track of currently infected community members and members with epidemiological links. When the teams are busy, the suspected patients are not examined at their addresses but are directed to the hospitals to undergo a viral test. The problem is that the majority of the epidemiologically linked individuals have to use public transportation to reach the hospital, despite the risk of spreading the virus. To overcome this, the mobile testing facilities can visit the neighborhoods where testing is needed, but the contact tracing teams are overly occupied. Mobile testing has a significant role and potential for increasing the number of viral tests and the availability of such tests, especially for the disadvantaged groups or COVID-19 clustered areas, by offering testing within walking distance. In addition, mobile testing provides a safer environment by reducing the contamination that occurs before and during the testing process, as community members do not have to travel to the hospitals and have a direct interaction with others.

The mobile system for sample collection and testing is observed to be efficient via its application in South Korea and the UK, the pioneer countries for this application. Inspired by that application, this paper proposes an efficient mobile sample collection system that utilizes temporary testing vehicles and the central health centers for sample collection and for providing the results of the collected samples. The primary purpose of the mobile sample collection is to increase the availability of the test to control and decrease the rate of transmission of COVID-19. For this purpose, the temporary testing centers visit districts and collect samples to be brought to the central hospital. This approach enables the temporary testing centers to continue their tours until the end of their working hours. The problem determines the tours of temporary testing centers and the length of stay for the temporary testing vehicles at each visited district within their respective routes. Even though this system is designed based on the current practices of the H+ Yangji Hospital Walk-Thru testing application in Gwanak-gu, it can be implemented in any country for sample collection.

Currently, testing has become easily accessible to a wide range of communities. For example, rapid tests are available in pharmacies in many countries; or there are currently 521 COVID-19 Authorized Diagnostic Laboratories in Turkey that are eligible for PCR testing. However, the availability of tests to this extent was not possible at the beginning of the pandemic. When the pandemic first hit, PCR testing could be conducted in only two cities in Turkey, which are Istanbul and Ankara. The testing and sample collection became widespread throughout the country in the later stages of the pandemic. Not only has Turkey struggled due to limited testing setups, but it was a common issue all around the globe. However, the speed of availability and accessibility of tests differ from country to country. As a result of our interviews, we realized that the UK and Seoul were the countries that handled the situation successfully during this pandemic since they aimed to increase the availability and accessibility of the testing as much as possible by using various testing strategies. Even though some countries managed to handle the challenges of the pandemic, there are countries that struggled with the process. More importantly, the pandemic is ongoing, with the risk of other outbreaks in the future emerging from variants of the virus. Therefore, a re-implementation of testing is vital to curb a possible outbreak. In our study, we aim to establish an exemplary mobile testing system to increase the accessibility of testing at the beginning of pandemics by compiling the testing strategies. In brief, the system and the results reported in this paper can easily be adopted by other countries for sample collection during a pandemic.

The remainder of the paper is organized as follows: Section 2 presents a formal problem definition, followed by a review of the related literature. Section 3 proposes a mathematical model for the proposed problem, and in section 4, the performance of the mathematical model is tested on small and large data sets. The small data set is a real data set obtained by the confirmed cases of districts of Seoul, Korea, and by interviews with health personnel of H+ Yangji Hospital. The large data set is constructed by 99 health centers from distinct neighborhoods of 22 districts of Istanbul, Turkey. In section 5, four math-heuristics proposed for the problem and tested on both data sets. Later, the results and the performance of the heuristics are compared with the results and performance of the mathematical model. Finally, the paper is concluded in Section 6 with a summary of the study.

2. Problem Definition and Related Literature

2.1. Problem Definition

This work proposes a mobile sample collection model inspired by the existing mobile systems applied worldwide. The proposed system has a predefined number of temporary testing vehicles, also called temporary screening centers, and a central health center/hospital responsible for testing all the collected samples. The system allows the mobile sample collection centers to stay at certain points near health centers and hospitals, such as parking spots, as a semi-mobile testing booth if the sample collection potential is sufficiently high. The sample collection potential in a location is defined as estimated number of people who are willing to provide samples per hour in that location. The temporary testing vehicles start their tours at the beginning of the day, departing from the depot, which is a central hospital. They visit several potential locations once they leave the depot. Since sample collection is vital to detect infections, a temporary testing vehicle may visit multiple locations during the day as long as there are unvisited locations with sample collection potential. The time the vehicle spends at the location also affects the total number of samples collected and thus must be decided on. To be close to real-life practices, the duration of the stay of vehicles is chosen as one-hour time blocks. In this case, temporary testing vehicles spend at least one hour at each visited location. If the sample potential of a location is high, a temporary testing vehicle can opt to stay at there for hours. We assume that the temporary testing vehicles work in "shifts" to represent the total duration a mobile vehicle can operate within the day. In order to evaluate the collected samples, the vehicles should return the specimens to the central hospitals' labs before the end of their shifts. According to the changing sample collection potential, the system can assign multiple locations to the vehicles to comply with the schedule. Figure 1 illustrates a possible tour for the temporary testing center of the proposed system, where temporary testing centers travel along geographically scattered nodes. The nodes which are within a predetermined distance to the visited nodes are assumed to be covered, i.e., people who reside close to the node visited by temporary testing centers are expected to travel to the visited node. Temporary testing vehicles are supplemental testing services; therefore, residents close to the hospitals can walk for sample collection rather than being visited by the temporary testing centers.

The sample collection potential will be high when temporary testing centers arrive in the district, and it is expected to diminish after a particular time. The diminishing potential over time encourages the vehicles to visit other points. In order to evaluate diminishing sample collection potential with respect to time, the shifts of vehicles are partitioned into two parts and a step function is formulated. It should be noted that while traveling between districts, the vehicles cannot collect samples during that interval. Therefore, too much mobility is not favored.

Another aspect of this system is that the people in the neighborhood of a visited district can walk for sample collection; this will be called 'coverage' throughout the paper. Therefore, collecting samples from non-visited points in districts within a specific distance by coverage is also possible. If a district is covered rather than visited, the sample collection is expected to be less due to fewer attendees walking to the visited district for testing purposes, as there is a correlation between the willingness of the patients of covered districts to reach the temporary testing centers and the distance to the visited district. This assumption is to comply with real-life practices. In addition to those assumptions, all vehicles return to the central health center/hospital to test the samples at the end of each day. It is possible to keep samples without spoilage for eight hours with adequate equipment in the mobile vehicles, thus, there will be an upper bound on the total journey time. In the proposed problem, these assumptions are given by the real-life applications of the mobile sample collection units.

As illustrated in Figure 1 the temporary testing centers travel through a geographically scattered set of nodes. In Figure 1, a temporary testing center departs from the central hospital, routes districts 3, 6, 7, and 10, and returns to the central hospital within the given available period. When the temporary testing center visits district 3, it stays in district 3 for some time. Residents of districts 2 and 4 can walk to district 3 for sample collection, since those districts are within the coverage radius of district 3. After a while, the temporary testing center moves from district 3 to district 6 and stays in district 6 there for a while. Since only district 5 is within the coverage radius of district 6, residents of district 5 can walk to district 6 for sample collection. Similarly, the temporary testing center moves to districts 7 and 10. Due to the coverage

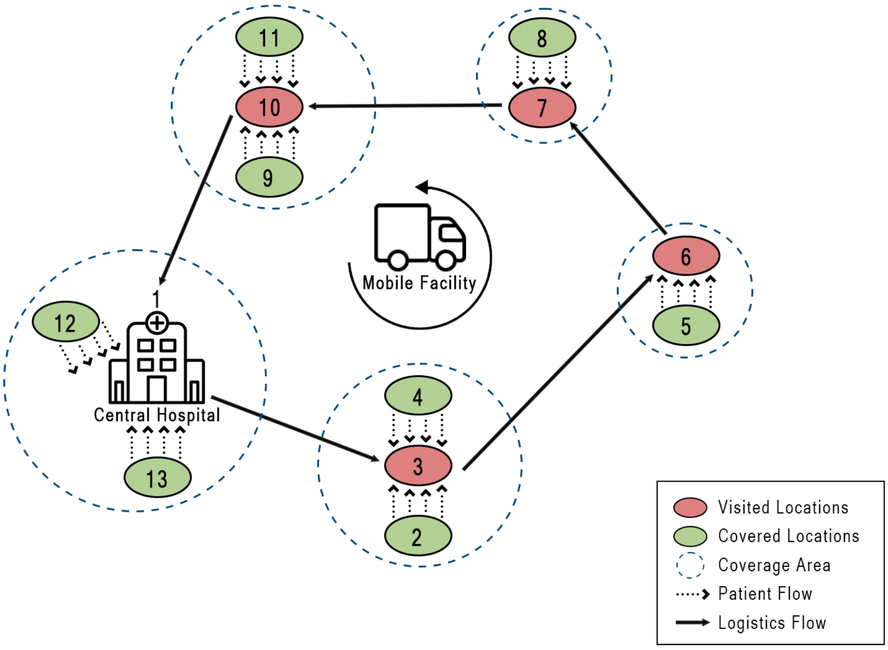


Figure 1: Schematic Illustration of the Tours of Temporary Testing Center of the Proposed System

radius of districts 7 and 10, it collects samples from district 8 during its stay in district 7 and from districts 9 and 11 during its stay in district 10. In addition, it should be noted that the central hospital is one of the possible locations where the temporary testing centers can stay to collect samples besides its responsibility of resulting the samples collected in vehicles throughout the day.

The proposed new system aims to enhance the availability of testing while also increasing the total sample collection and alleviating the testing responsibility of the traditional testing centers. Thus, the main decisions are taken via the system as follows:

- the locations to be visited among candidate visiting points
- the length of stay of the temporary testing vehicles
- the tours of temporary testing vehicles

In the proposed problem, the primary performance measure is considered as the maximization of the total sample collection to reach as many the members of the community. Since the tours are constructed to include visiting multiple stops without the obligation to visit all stops, our problem can be classified as a variant of the Selective Vehicle Routing Problem with coverage considerations and time blocks. To the best of the authors' knowledge, this version of the Selective Vehicle Routing Problem has not been characterized in the literature.

2.2. Related Literature

For the proposed system in our paper, the primary consideration for the logistic management of temporary testing centers is to increase the availability of COVID-19 viral testing. Increasing availability implies reaching as many suspected sick people as possible. In this section, our proposed problem will be analyzed under three categories within the literature. Firstly, it will be analyzed within the perspective of routing literature through the problem dynamics so that the novelty of the study will be highlighted. Later, the problem will be analyzed in the literature of epidemic/pandemic related studies since our study includes mobile units in the context of COVID-19 pandemic. Moreover, gradual decay functions will be investigated within the literature involving the gradual decay functions due to demand variation in terms of time and coverage.

2.2.1. Related Routing Literature

Routing problems were introduced to find optimal routes among the vertices on a graph. Rather than serving every vertex, the problems that are restricted with a budget, profit, or route length to serve a subset of vertices are generally referred to as Routing Problems with Profits or Selective Routing Problems. Two significant performance measures for those problems are maximization of profit and minimization of tour cost. This section will focus on the variants related to our problem dynamics. Tsiligiridis (1984) proposed Orienteering Problems for selecting the nodes to be visited to maximize the collected profits within a time constraint. The problem is also known as the Selective Traveling Salesman Problem. Butt and Cavalier (1994) proposed its multi-vehicle version called Team Orienteering Problem. The problem is widely studied in the literature with different variations. If the problem is formulated with a prize collection threshold while minimizing the tour length and the cost of excluding nodes at the same time, then it is called the Prize Collecting Traveling Salesman Problem (Fischetti and Toth, 1988). Moreover, the problem is defined as Quota TSP (Awerbuch et al., 1998) if the cost of excluding nodes is given as zero. When the two significant performance measures are combined in the objective function, the problem is called the Profitable Tour Problem (Bienstock et al., 1993). The problem offers the flexibility to set some locations as more critical than others. More recently, Erdogan et al. (2010) introduced the Attractive Traveling Salesman Problem to maximize the tour profit derived from the customer vertices, measured by the attraction function. Also, Erdogan and Laporte (2013) proposed an Orienteering problem with variable profits, in which profit collected increases if the number of visits to a node increases or the duration of stay in a node increases. For the interested readers, Vansteenwegen and Souffriau (2011) and Gunawan et al. (2016) are the recent studies presenting a comprehensive survey about the selective routing problems and their variants, including problem descriptions and solution approaches.

In the health-care context, Halper and Raghavan (2011) determine routes for mobile facilities to maximize the amount of demand serviced. More interestingly, the demand for the service provided varies over time and the mobile facility cannot provide service in transit, similar to our assumption. Our study can be seen as an extension of this study regarding the maximum amount of time that mobile facilities can spend in the system. Moreover, Şahinyazan et al. (2015) developed a mobile system consisting of bloodmobiles and shuttles to deliver the collected blood to increase blood collection in Ankara and Istanbul. They proposed a new model called Selective Vehicle Routing Problem with Integrated Tours to maximize blood collection levels and minimize the logistics cost of collecting a pre-determined blood level. Salman et al. (2021) developed a mathematical model for routing mobile clinics with various services for the Syrian migrant farm-workers in Malatya and Rize, Turkey. They considered three hierarchical objectives: coverage, number of vehicles, and travel cost. Even though Şahinyazan et al. (2015) and Salman et al. (2021) are the closest studies to our study, they do not satisfy all the aspects of our problem. They do not simultaneously include the non-linear demand rate concerning coverage and time aspects, therefore, our problem is a novel approach in the selective routing context. The classification of routing problems with profits is summarized in Table 1.

Since providing the viral testing service to a broader area helps to limit the outbreak, serving only specific areas to maximize profit is not acceptable. In this way, people in more locations can be kept under control while confirming the positive cases within a larger area. In this section, we will further focus on the variants of coverage problems related to our problem dynamics. In such context, Covering Salesman Problem proposed by Current and Schilling (1989) is another relevant work for our study. The problem identifies a minimum cost tour so that nodes not included in the tour are within some predetermined coverage distance of the nodes in the tour. In this problem setting, every node is restricted to be covered. Therefore, it does not allow selective routing, but forces coverage. In addition, a generalized version is proposed by Golden et al. (2012) where each node needs to be covered at least a predetermined time. The path version of Covering Salesman

Table 1: The Routing Problems with Profits

Problem	Vehicle	Multi-Period	Coverage	Selective Routing	Time Consideration	Time Buckets	Objective	Constraint	Capacity Consideration
Our Problem	Multi	×	Not guaranteed	✓	✓ (time duration)	✓	Max Profit / Min max walking distance	Time shifts and duration	×
Tsiligiridis (1984)	Single	×	×	✓	✓ (time duration)	×	Max profit	Upper time duration	×
Fischetti and Toth (1988)	Single	×	×	✓	×	×	Min total distance (and penalty of unvisited nodes)	Prize collection threshold	×
Bienstock et al. (1993)	Single	×	×	✓	×	×	Max (profit-cost)	-	×
Butt and Cavalier (1994)	Multi	×	×	✓	✓ (time duration)	×	Max profit	Upper time duration	×
Awerbuch et al. (1998)	Single	×	×	✓	×	×	Min cost	Prize collection threshold	×
Erdogan et al. (2010)	Single	×	×	✓	✓ (time duration)	×	Max profit	Upper time duration	×
Halper and Raghavan (2011)	Single and Multi	✓	×	✓	✓ (continuous-time planning horizon)	×	Max demand covered	Travel Time Constraint	✓
Erdogan and Laporte (2013)	Single	×	×	✓	✓ (time duration)	×	Max profit	Passage or Time threshold	×
Şahinyazan et al. (2015)	Multi	✓	Not guaranteed	✓	✓ (planning horizon)	×	Min Cost	Sample collection threshold	×
Salman et al. (2021)	Multi	✓	Not guaranteed	✓	✓ (planning horizon)	×	Max Coverage/Min number of vehicles/Min travel cost	Service level threshold	×

× , denotes that the problem does not include the property.
✓, denotes that the problem includes the property.

is also proposed by Current et al. (1984). Another well-known related problem is the Covering Tour Problem proposed by Gendreau et al. (1997) where all nodes are either visited or covered by being sufficiently close to a single vehicle, while the objective is to minimize the tour length. In the Multivehicle Covering Tour Problem (Hachicha et al., 2000), the coverage is obtained with multiple vehicles. As emphasized, it is impossible to visit all possible locations due to time limitations. Also, Karaoğlan et al. (2018) introduced the multivehicle covering tour problem with probabilistic coverage. In this problem, a visited vertex can fully serve another vertex with a given probability. They provided a nonlinear integer programming model and a linearization scheme for the objective function.

Moreover, Hodgson et al. (1998) decided to utilize mobile healthcare facilities to increase the accessibility of primary healthcare resources in the Suhum District of Ghana. They propose a Covering Tour Problem to minimize tour cost, the number of stops covered by the tour, and maximize the total population on tour. Hachicha et al. (2000) also examines the mobile healthcare facilities by limiting the number of nodes visited on a route and the length of each route. Doerner et al. (2007) extend the previous studies by Hachicha et al. (2000) and Hodgson et al. (1998) to multi-objective formulation considering the effectiveness of workforce employment, average accessibility, and coverage as criteria. Further, Allahyari et al. (2015) developed a multi-depot covering tour problem to minimize the total routing and allocation costs of mobile health centers. The classification of covering problems is summarized in the Table 2.

The Selective Routing Problem complies with the characteristics of our problem for determining the tours of temporary testing centers, as it selects a subset of nodes to serve and maximizes the total sample collection. Further, the collected sample is required to be transferred to a hospital by the end of the shift to avoid spoilage. However, there are additional aspects introduced in the context of our problem. Our problem has coverage characteristics and diminishing sample collection potentials, which are included in restraining from selecting solely favorable locations, therefore, reaching more districts. Moreover, there are time blocks for real-life applications in which the potential samples at each node will not be collected at once. Thus, using a simple variant of the Selective Vehicle Routing Problem will not be sufficient to cover all features of our problem.

Furthermore, the Covering Tour Problem also complies with our aim of serving as many residents, therefore, increasing the availability of testing by coverage, since it considers reaching every node either by visiting or being sufficiently close. However, unlike the Covering Tour Problem, the focus is on maximizing the collection of samples, and a decision must also be made regarding the time duration. Our problem also does not entail an obligation to reach all nodes. Thus, using a simple variant of the Covering Tour Problem will not be adequate to cover all characteristics of the problem. In this study, we decide the tours and the length of stay of the temporary testing vehicles by the model. Therefore, we adopt an extension of Covering Tour and Selective Vehicle Routing approaches and combine it with coverage and time-dependent sample collection potential.

2.2.2. Epidemic/Pandemic Related Literature

In the OR literature, there are pandemic-related studies curbing the outbreaks while using the scarce capacity and resources. Sun et al. (2014) proposed linear programming models for patient and resource allocation with the objectives of minimizing the total travel distance to hospitals and the maximum travel distance of a patient to a hospital during a pandemic influenza outbreak. Yarmand et al. (2014) proposed a two-stage stochastic linear programming model for a two-phase optimal vaccine allocation procedure in a case of an outbreak. Büyüktahtakın et al. (2018) proposed an epidemics-logistics mixed-integer linear optimization model deciding on the timing, amount, and location of source allocation to minimize the total number of infections and fatalities under a budget and a multi-planning horizon for the Ebola epidemic.

Recent studies about COVID-19 provide a methodology to allocate scarce resources such as testing materials. Due to the nonlinear inheritance of the pandemic progress within a population, nonlinear models are proposed to imitate the critical characteristic of disease transmission and nonlinear transition dynamics. Buhat et al. (2021) introduces a nonlinear programming model for allocating limited COVID-19 test kits to

Table 2: The Covering Routing Problems

Problem	**Vehicle**	**Multi-Period**	**Coverage**	**Selective Routing**	**Time Consideration**	**Time Buckets**	**Objective**	**Constraint**	**Capacity Consideration**
Our Problem	Multi	×	Not guaranteed	✓	✓ (time duration)	✓	Max Profit / Min max walking distance	Time shifts and duration	×
Current and Schilling (1989)	Single	×	✓	×	×	×	Min Tour Cost	Coverage Constraint	×
Gendreau et al. (1997)	Single	×	✓	×	×	×	Min Tour Cost	Coverage Constraint	×
Hodgson et al. (1998)	Single	×	✓	×	×	×	Min Tour Cost	Coverage Constraint	×
Hachicha et al. (2000)	Multi	×	✓	×	×	×	Min Tour Cost	Coverage Constraint Bound on total minimum length	×
Doerner et al. (2007)	Multi	×	✓	×	×	×	Min Effectiveness of workforce employment/Average accessibility/Coverage	Coverage Constraint	×
Golden et al. (2012)	Single	×	✓	×	×	×	Min Tour Cost	Coverage Constraint (Visit nodes more than once)	×
Allahyari et al. (2015)	Multi	×	✓	×	×	×	Min total routing and allocation costs	Coverage Constraint and Capacity Constraint	✓
Karaoğlan et al. (2018)	Multi	×	✓ (Probabilistic Coverage)	×	✓ (Distance Limit)	×	Max the expected customer demand served	Distance constraint	×

× , denotes that the problem does not include the property.
✓, denotes that the problem includes the property.

the fixed and large testing centers within the equity perspective, capacity, and populations. They estimate the number of infected people, compute testing accessibility and distribute the test kits accordingly. In order to increase the availability of testing, they emphasize test kit allocation to fixed test centers and the strategic location of additional fixed testing centers. Furthermore, Abdin et al. (2023) provide a nonlinear programming model for allocating COVID-19 testing materials to minimize the spread of the pandemic. They specifically consider the mobility of infected and non-infected asymptomatic individuals between the regions and consider the positivity rate of testing via model predictions fitting closely to the real data. Those studies evaluate the healthcare system's capacity allocation problems during the pandemic and emphasize data fitting for pandemic progress. Unlike our study, they do not propose a mobile vehicle system and include demand variation concerning time and coverage within the model. Our study deviates from the other related studies in epidemic and pandemic-related literature due to the mobile dynamics of the testing strategy used, and the nonlinear demand variation included within the mathematical model.

2.2.3. Gradual Decay Functions

In our problem, the sample collection potential of the vertices diminishes if a vertex is covered rather than visited. Moreover, the sample collection potential is expected to decrease after a while and is defined as a function of time, i.e. decay gradually for both visited and covered vertices. In this section, we investigate the studies including gradual decay functions in the literature.

In covering problems, basically, binary coverage is assumed. It implies that a node is either fully covered or not covered. The full coverage implies that the distance of a node from the visited node is less than a predefined value. Also, a node is not covered if the distance is bigger than a predefined value. This basic assumption is later generalized throughout the literature via the concept of gradual decay functions. Church and Roberts (1983) proposed partial coverage concerning the distance. Berman and Krass (2002) proposed a generalized maximal cover location problem with partial coverage as a decreasing step function of the distance. Further, Berman et al. (2003) introduced a gradual coverage decay model with two coverage radii. None of the demand in a node is covered if the visited node is beyond the upper coverage radius. Within the lower coverage radius, the demand in a node is fully covered. For a coverage radius between lower and upper coverage radius, the demand covered gradually decreases from full coverage to no coverage with increasing coverage radius. Also, Karasakal and Karasakal (2004) proposed a Lagrangean relaxation-based solution approach to solve the p-median problem with gradual decay function defined as a monotone decreasing function of the distance between facility site and demand point.

Drezner et al. (2004) considered gradual coverage assumption while maximizing total population covered within facility location context. Later, the stochastic version of the problem is proposed by Drezner et al. (2010). In this setting, the random variables are the minimum and maximum distances of the gradual coverage. Within the literature of maximal cover location problem, the gradual coverage has been studied extensively. For instance, Berman et al. (2018) aims to maximize the joint partial coverage by several facilities while Karatas (2017) studied multi-objective facility location problem with cooperative and gradual coverage. Recently, Karatas and Eriskin (2021) and Khatami and Salehipour (2022) studied gradual decay functions. Karatas and Eriskin (2021) studied gradual and cooperative minimal covering location problem. They allowed capacitated facilities with variable coverage radii. A gradual minimum covering location problem with distance constraints has been proposed by Khatami and Salehipour (2022). They aim to minimize the total coverage of vertices while locating a fixed number of undesirable facilities.

In the healthcare setting, the gradual decay functions are also utilized to represent the survival rates. For instance, Erkut et al. (2008) included a survival function in covering models for emergency medical services. The survival function is defined as a monotonically decreasing response time function. Their main aim is to maximize the expected number of survivors. In their work, there is only one survival function since they consider only one class of patients. Later, Knight et al. (2012) extended their work by including multiple classes of survival functions regarding multiple classes of patients. Moreover, Şahinyazan et al. (2015) considered a mobile blood collection system, and the blood potentials of the nodes are defined as a decreasing function.

In the literature, it is recognized that the gradual coverage is mostly represented via uniform decay functions and step functions. Our problem considers diminishing sample collection potential if a node is covered. Moreover, we include diminishing sample collection potential of both visited and covered nodes as a function of time. For simplicity, a step function is chosen to model the diminishing sample collection potential over time.

2.3. Our Problem in the Literature

To the best of our knowledge, there is no study in literature that captures all aspects of the problem considered.

In summary, our contributions:

- This study proposes a novel mobile testing system that is time and coverage dependent demand variation complying with the COVID-19 aspects based on the interviews with the authorities.
- The sample (prize) collection is handled in time blocks rather than at once, and depends on the coverage and duration of vehicles staying at a location, which is decided via the model. The sample collection potential diminishes if a node is covered rather than visited, and the sample collection potentials of visited and covered nodes are defined as a step function of time.
- Our new problem shares similar characteristics with Selective Vehicle Routing Problems and Covering Tour Problems in the literature. However, when we incorporate duration decisions, this problem corresponds to a novel formulation that enables its introduction to the literature as a new variant of those problems. The diminishing sample collection with respect to time and distance distinguishes this new problem while modeling the mobile sample collection system
- We propose a mathematical formulation where the route and the time spent at each visited location are determined via the model. Moreover, we designed four two-stage heuristic approaches yielding satisfactory solutions for large instances. The heuristic approaches are distinguished by the differences in the location decisions that are fed to the mathematical model.
- Extensive computational analysis is conducted to test the performance of the solution methods developed with small and large data sets constructed.

3. Model Development

Let $G = (N, A)$ be the network, where N is the set of possible locations for temporary testing centers and A represents the road segments. Let K be the set of m identical temporary testing vehicles in the system. The node 1 is the designated as central laboratory location; it is named the depot node. The depot node is chosen to comply with the characteristics of other hospital locations and according to the geographical position. c_{ij} represents the distance between node i and node j as calculated by the spherical law of cosines using the coordinates of the possible locations.

The initial sample collection potential of node i is b_i. We assume that the number of confirmed cases of the districts is directly proportional to the testing potentials of the districts. b_i is obtained considering the district's confirmed cases, which possible location it is in, and the number of collected samples in the mobile booth application. The sample collection potentials of the nodes are expected to diminish depending on whether the nodes are directly visited or being covered and depending on the time that the temporary testing vehicle stays there.

In terms of definition, the sample collection potential refers to the number of people willing to provide a sample per hour and this potential is expected to diminish gradually. According to the interviews, health workers in hospitals report that in the morning shift (8.30 am-1.30 pm), the sample collection is higher than in the afternoon shift (1.30 pm- 5.30 pm). In order to get the results of the test during the day, labs in the hospitals accept the samples during the morning shift. However, the results are announced the next day if the lab receives the sample in the afternoon. Therefore, more people tend to provide samples on the morning shift. We adopt this behavior to the practice of mobile testing vehicles with slight modification since temporary testing centers are mobile. We assume that as soon as people discover the arrival of a mobile vehicle, they will want to receive the service immediately. In addition, we assume that when the mobile vehicle arrival is announced, people will show interest in the mobile vehicles and also provide samples during the day. Rather than the time of the clock that a vehicle arrives at a location, the duration of the vehicle staying at a location affects the sample collection time. In order to illustrate this behavior, we develop a step function that represents the sample collection potentials for nodes.

A vehicle can stay at a location at most by the time it can operate within a day, denoted by the parameter S. Then, the shift is divided into two parts to highlight the decrease in the number of people providing samples. This behavior implies that the sample collection potential of a node on the second part of the shift is less than that on the first part of the shift. With the assumptions stated previously, to model this behavior we develop a step function that represents the sample collection potentials for visited nodes. If a temporary testing vehicle stays in a location for more than T hours, fewer people will provide samples per hour, decreasing the sample collection potential. A parameter, β, in the $[0,1]$ interval reflects the reduction in the sample collection potential after a predefined time interval, T. For instance, a temporary testing center visits location i and stays in the same location for t hours before visiting another location. We have two cases to consider: $t \leq T$ and $t > T$. If $t \leq T$, then the total sample collected from that visited location i will be $t \times b_i$. However, if $t > T$, then the total sample collected from that visited location i will be $T \times b_i + (t - T) \times \beta \times b_i$. Then, the hourly sample collection potential of a visited node $i \in N$ is defined as follows:

$$\text{Hourly sample collection potential of a visited node } i = \begin{cases} b_i & \text{for } [0,T] \\ \beta \times b_i & \text{for } (T,S] \end{cases}$$

Recall that it is assumed that the people in the neighborhood of a visited node can walk for sample collection. Another parameter, α, in the $[0,1]$ interval is defined to reflect the change in sample collection potential if a location is covered. In other words, this parameter reflects the decrease in the sample collection if the nodes are covered by being sufficiently close. Being sufficiently close means that the distance between node i and node j is smaller or equal to a predefined distance (5 km). The relation is denoted by availability matrix a_{ij} and it should be noted that the matrix is symmetric. For instance, a temporary testing center visits location i, and the distance between location i and another location j is smaller or equal to a predefined value. In addition, the temporary testing center stays in the location i for t hours before visiting another location. Since location i is available to location j, people from location j walk to the temporary testing center at location i to provide a sample. We have again two cases to consider: $t \leq T$ and $t > T$. If $t \leq T$, then the total sample collected from that covered location j will be $t \times b_j \times a_{ij} \times \alpha$. However, if $t > T$, then the total sample collected from that covered location j will be $T \times \alpha \times a_{ij} \times b_j + (t - T) \times \beta \times \alpha \times a_{ij} \times b_j$.

Then, the hourly sample potential of a covered node $j \in N$ is defined as follows:

$$\text{Hourly sample collection potential of a covered node } j = \begin{cases} \alpha \times a_{ij} \times b_j & \text{for } [0,T] \\ \beta \times \alpha \times a_{ij} \times b_j & \text{for } (T,S] \end{cases}$$

A comprehensive sensitivity analysis of the β, α, and T values is conducted in Section 4. In our model, the duration of stays on different parts of the shits are decided via decision variables z^1_{ik} and z^2_{ik}. In accordance with the previous examples, t denotes the time spent at a location. In the case of $t < T$, t denotes the time spent at a location in the first part of the shift. Also, it is decided via z^1_{ik} through the expression $\min\{T, z_{ik}\}$. On the other hand, in the case of $t > T$, $t - T$ denotes the time spent at a location in the second part of the shift. In this case, $t - T$ is decided via z^2_{ik} through the expression $\max\{0, z_{ik} - T\}$. Furthermore, since t denotes the total time spent at a location, it is denoted as the summation of z^1_{ik} and z^2_{ik} and decided by z_{ik} in the model. Finally, the maximization of the total sample collection is introduced as the performance measure for the proposed problem. It should be noted that the sample collection will be referred to as the output of the activity or the objective function of the mathematical model. On the other hand, the sample collection potential will be referred as an input data for the activity or parameter for the proposed problem. Problem parameters and decision variables are defined in Table 3 and Table 4, respectively.

Table 3: Parameters

Parameters	
m	The total number of temporary testing centers to be planned
p	The maximum number of locations that can be visited by any booth. If p is not specified, then $p = \lvert N \rvert$
α	Sample collection potential change due to coverage $\in [0,1]$
β	Sample collection potential change over time $\in [0,1]$
c_{ij}	The distance between $i \in N$ and $j \in N$ (km)
a_{ij}	$\begin{cases} 1 & \text{if } i \in N \text{ can cover } j \in N \\ 0 & \text{otherwise} \end{cases}$
b_i	Hourly sample collection potential of location $i \in N$
T	Time indicated to switch to the next part of the shift (h)
S	Length of the shift (h)
sp	Speed of the temporary testing centers (km/h)

Table 4: Decision Variables

Decision Variables	
X_{ijk}	$\begin{cases} 1 & \text{if location } j \in N \text{ is visited right after location } i \in N \text{ by the temporary testing center } k \in K \\ 0 & \text{otherwise} \end{cases}$
y_{ik}	$\begin{cases} 1 & \text{if location } i \in N \text{ is provided testing service by temporary testing center } k \in K \\ 0 & \text{otherwise} \end{cases}$
u_{ik}	auxiliary variables to eliminate sub-tours where $i \in N$, $k \in K$
z_{ik}	number of one-hour intervals that are spent in location $i \in N$ by temporary testing center $k \in K$
z^1_{ik}	$\min\{T, z_{ik}\}$, the number of hours that temporary testing center $k \in K$ stays in location $i \in N$ in the first part of the shift.
z^2_{ik}	$\max\{0, z_{ik} - T\}$, the number of hours that temporary testing center $k \in K$ stays in location $i \in N$ in the second part of the shift.

The proposed model is formulated in a naive way as follows:

$$\begin{aligned} \max \quad & \sum_{i\in N}\sum_{k\in K}(b_i \times z^1_{ik} + \beta \times b_i \times z^2_{ik}) \\ & + \sum_{i\in N}\sum_{j\in N, i\neq j}\sum_{k\in K}(\alpha \times a_{ij} \times b_j \times z^1_{ik} + \beta \times \alpha \times a_{ij} \times b_j \times z^2_{ik}) \end{aligned} \tag{1}$$

subject to

$$\sum_{i\in N}\sum_{j\in N, i\neq j}(1/sp) \times c_{ij} \times X_{ijk} + \sum_{i\in N} z_{ik} \leq S \quad \forall k \in K \tag{2}$$

$$z_{ik} = z^1_{ik} + z^2_{ik} \quad \forall k \in K, i \in N \tag{3}$$

$$z^1_{ik} \leq T \quad \forall k \in K, i \in N \tag{4}$$

$$z^1_{ik} \leq z_{ik} \quad \forall k \in K, i \in N \tag{5}$$

$$z^2_{ik} \geq 0 \quad \forall k \in K, i \in N \tag{6}$$

$$z^2_{ik} \geq z_{ik} - T \quad \forall k \in K, i \in N \tag{7}$$

$$z_{ik} \leq S \times y_{ik} \quad \forall k \in K, i \in N \tag{8}$$

$$z_{ik} \geq y_{ik} \quad \forall k \in K, i \in N \tag{9}$$

$$\sum_{k\in K} y_{ik} + \sum_{k\in K}\sum_{j\in N: j\neq i} a_{ij} \times y_{jk} \leq 1 \quad \forall i \in N \tag{10}$$

$$\sum_{k\in K} y_{ik} \leq 1 \quad \forall i \in N \tag{11}$$

$$\sum_{i\in N:i\neq 1} X_{i1k} = 1 \quad \forall k \in K \tag{12}$$

$$\sum_{i\in N:i\neq 1} X_{1ik} = 1 \quad \forall k \in K \tag{13}$$

$$\sum_{i\in N:i\neq j} X_{ijk} = y_{jk} \quad \forall k \in K, j \in N/\{1\} \tag{14}$$

$$\sum_{i\in N:i\neq j} X_{jik} = y_{jk} \quad \forall k \in K, j \in N/\{1\} \tag{15}$$

$$u_{ik} - u_{jk} + pX_{ijk} \leq p - 1 \quad \forall 2 \leq i \neq j \leq p, \forall k \in K \tag{16}$$

$$u_{ik} \geq y_{ik} \quad \forall i \in N, k \in K \tag{17}$$

$$X_{ijk}, y_{ik} \in \{0, 1\} \quad \forall i \in N, j \in N, k \in K \tag{18}$$

$$u_{ik}, z_{ik}, z^1_{ik}, z^2_{ik} \geq 0 \quad \textit{integer} \quad \forall i \in N, k \in K \tag{19}$$

As mentioned earlier, the primary performance measure is to maximize the total sample collection which is given by equation (1). The first part of the objective function represents the sample collection potential of a visited node i. The second term considers the samples collected only from locations j covered when the temporary testing center is visiting location i. The objective reflects the diminishing sample collection over coverage and time through α and β parameters, respectively. Constraint set (2) is to ensure that the temporary testing centers tour is completed by the end of the shift. The tour time includes the travel time and the service time in the locations. The time spent in the nodes is based on one-hour intervals to comply with the real-life practices. Constraint set (3) preserves the balance so that the first part of the shift and the second part of the shift add up to the length of the shift. Constraint sets (4)-(5), (6)-(7) are to linearize the expression $\min\{T, z_{ik}\}$ and $\max\{0, z_{ik} - T\}$, respectively. The expression $\min\{T, z_{ik}\}$ represents the duration of stays at a location in the first part of the shift while $\max\{0, z_{ik} - T\}$ represents the duration of stays at a location in the second part of the shift. Constraint set (8) is to ensure the stay of the temporary testing centers is shorter than the length of the shift. Constraint set (9) is to ensure the length of the stay of the temporary testing centers is at least one hour if the node is visited. Constraint set (10) is to ensure several aspects. Firstly, the constraint set does not force all locations to be served. Secondly, if a node is visited, then another node within its coverage radius cannot be visited. The latter is to prevent the testing centers from piling on an area with the highest sample collection potential to boost the sample collection potential. Instead, the aim is to increase availability by providing the testing service by reaching different areas while still having high sample collection. Constraint set (11) is to prevent multiple temporary testing centers from visiting the same location. Constraint sets (12)-(15) are to construct the tours of temporary testing centers. The vehicles leave the depot node, but the other nodes are only included in the tour if they are visited. Constraint set (16) is to represent Miller-Tucker-Zemlin (MTZ) sub-tour elimination constraints (Miller et al., 1960) for the testing center tours. Constraint set (17) is also related to the MTZ constraints. It implies that the auxiliary variables u_{ik} should be positive only if node i is visited. Constraints (18)-(19) are domain constraints.

4. Computational Analysis

Computational experiments are tested on two datasets, Seoul data as a small network and Istanbul data as a challenging network. The parameter b_i is obtained for both data sets through governmental websites such as Seoul Metropolitan Government (2022) and Turkish Statistical Institute (2021). The first set is constructed by the briefing reports containing the confirmed cases of the districts of Seoul, Korea, and by the interview of health personnel of H+ Yangji Hospital COVID-19 semi-mobile booth application (H + Yangji Hospital, 2021). The parameter b_i for the Seoul data is obtained through briefing reports of the confirmed cases of the districts (Seoul Metropolitan Government, 2022) and the number of collected samples in the mobile booth application (H + Yangji Hospital, 2021). The data include the temporary testing centers' sample collection potentials of 25 districts of Seoul, Korea. In total, 25 hospital/health center locations are chosen from the COVID-19 screening clinics stated on the Seoul Metropolitan Government website (Seoul

Metropolitan Government, 2022). The depot node is chosen due to its geographical position and the fact that it is a large medical research institution. The possible temporary center locations are shown on the map in Figure 2.

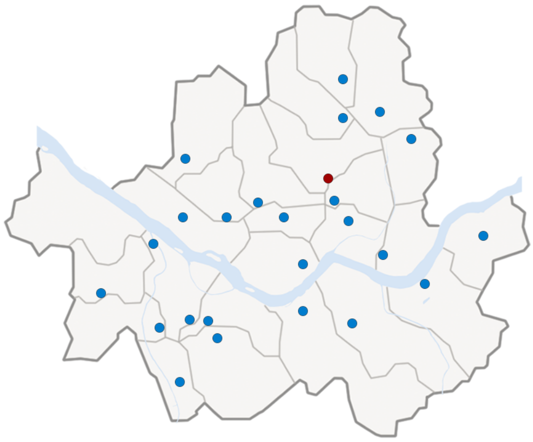


Figure 2: Potential Locations in Seoul, South Korea (red point represents the depot)

The second data set is constructed by 99 hospital/health centers from distinct neighborhoods of 22 districts of Istanbul, Turkey. These districts are prioritized due to their quality of life indexes (Şeker, 2015). For the Istanbul case, the daily sample collection potential is assumed to be equal to the neighborhood population of the hospital/health center. The parameter b_i for the Istanbul data is obtained by the population data of districts in Istanbul taken from Turkish Statistical Institute (2021). The depot node is chosen as a long-established hospital in the Fatih district, which is considered the central district of Istanbul. The possible temporary center locations are shown on the map in Figure 3. The distances between the nodes are calculated by using the locations' coordinates. The predefined distance for availability is 5 kilometers. We consider the shift to be 8 hours and the first and second halves of the shifts to be 4 hours due to the common practices. All computations are performed on an Intel Xeon Silver 4210 with 14 gigabytes RAM. The MIP model is solved using CPLEX version 12.10.0.

4.1. Base case analysis for Seoul and Istanbul instances

The proposed mathematical model is utilized to solve the instances of Seoul, South Korea and Istanbul, Turkey. For both cases, we take three temporary testing centers for the base case with $\alpha = 0.5$ and $\beta = 0.5$. The optimal values and CPU times obtained from preliminary analysis for the Seoul and Istanbul are given in Table 5. Moreover, more detailed solutions for Seoul and Istanbul cases regarding location, routing decisions and and length of stays are given Figures 4 and 5. In both figures, node 1 denotes the hospital where vehicles depart at the beginning of the day and return at the end. As can be seen from the figures, the largest sample collections occurred with larger walking distances. The largest sample collections occurred at nodes 6 and 29 for Seoul and Istanbul, respectively. For the Seoul case, 41.97% of the samples are collected while covering nodes within the walking distance of 4.99 km. Similarly, 50.63% of the samples are collected while covering nodes within the walking distance of 4.29 km for the Istanbul case. Furthermore, the lowest sample collections occurred with smaller walking distances. The lowest sample collections occurred at nodes

Figure 3: Potential Locations in Istanbul, Turkey (red point represents the depot)

10 and 87 for Seoul and Istanbul, respectively. For the Seoul case, 5.6% of the samples are collected while covering nodes within the walking distance of 2.55 km. Similarly, 9.82% of the samples are collected while covering nodes within the walking distance of 3.65 km for the Istanbul case. It should be noted that 3.65 km and 2.55 km are the lowest values obtained for maximum walking distances for Seoul and Istanbul cases. Moreover, 4.99 km is the highest value obtained for the maximum walking distance for the Istanbul case. Further, 4.29 km is the second-largest value obtained for the maximum walking distance for the Seoul case. It can be observed that the range of maximum walking distance values is remarkable, therefore, it may have an influence on the patients' decision of utilizing the testing facilities. Since attendees from covered nodes are expected to arrive at the testing sites on their own, the maximum walking distance is worth analyzing its effect on sample collection as a second performance measure.

	The total number of temporary testing centers to be planned (m)	Sample collection potential change due to coverage (α)	Sample collection potential change over time (β)	Objective	CPU Time (seconds)
Seoul,South Korea	3	0.5	0.5	224 (sample)	0.54
Istanbul, Turkey	3	0.5	0.5	552,507 (sample)	41.18

Table 5: The Results of Seoul and Istanbul Case for the Base Cases

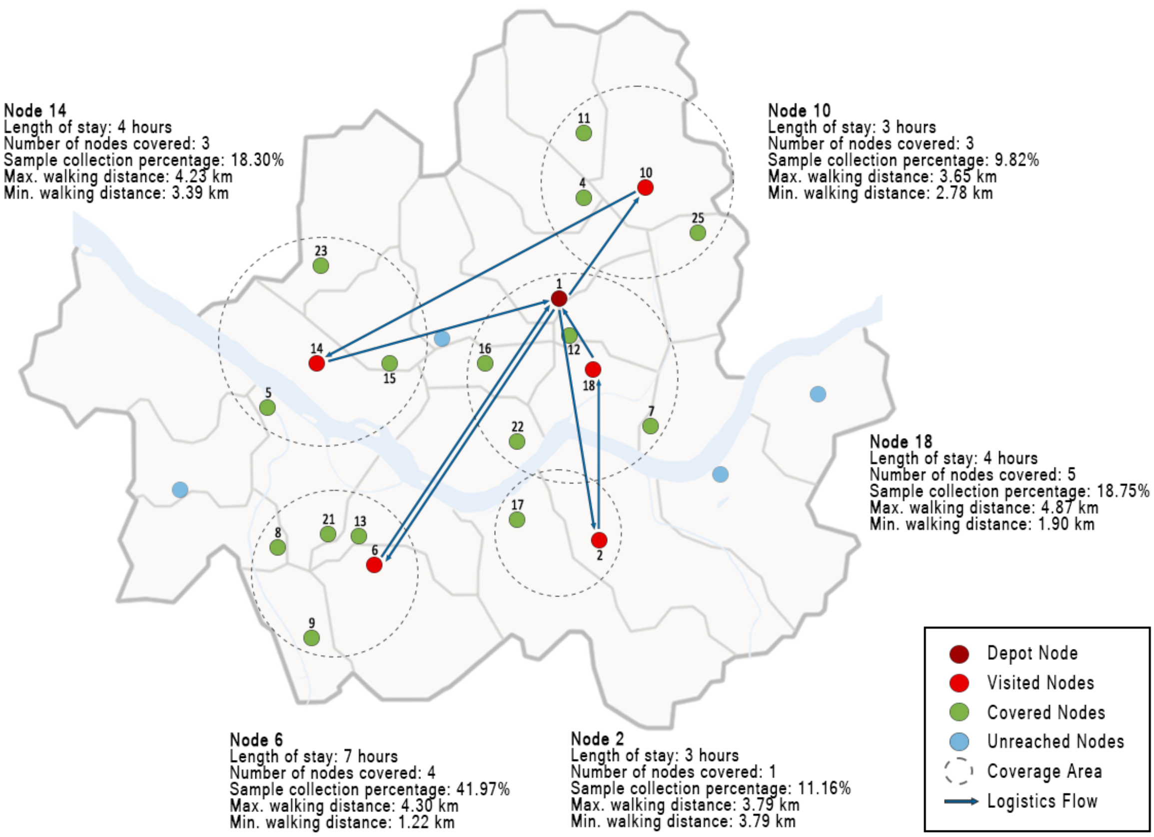


Figure 4: The Solution for Seoul Case for the Maximization of Total Sample Collection

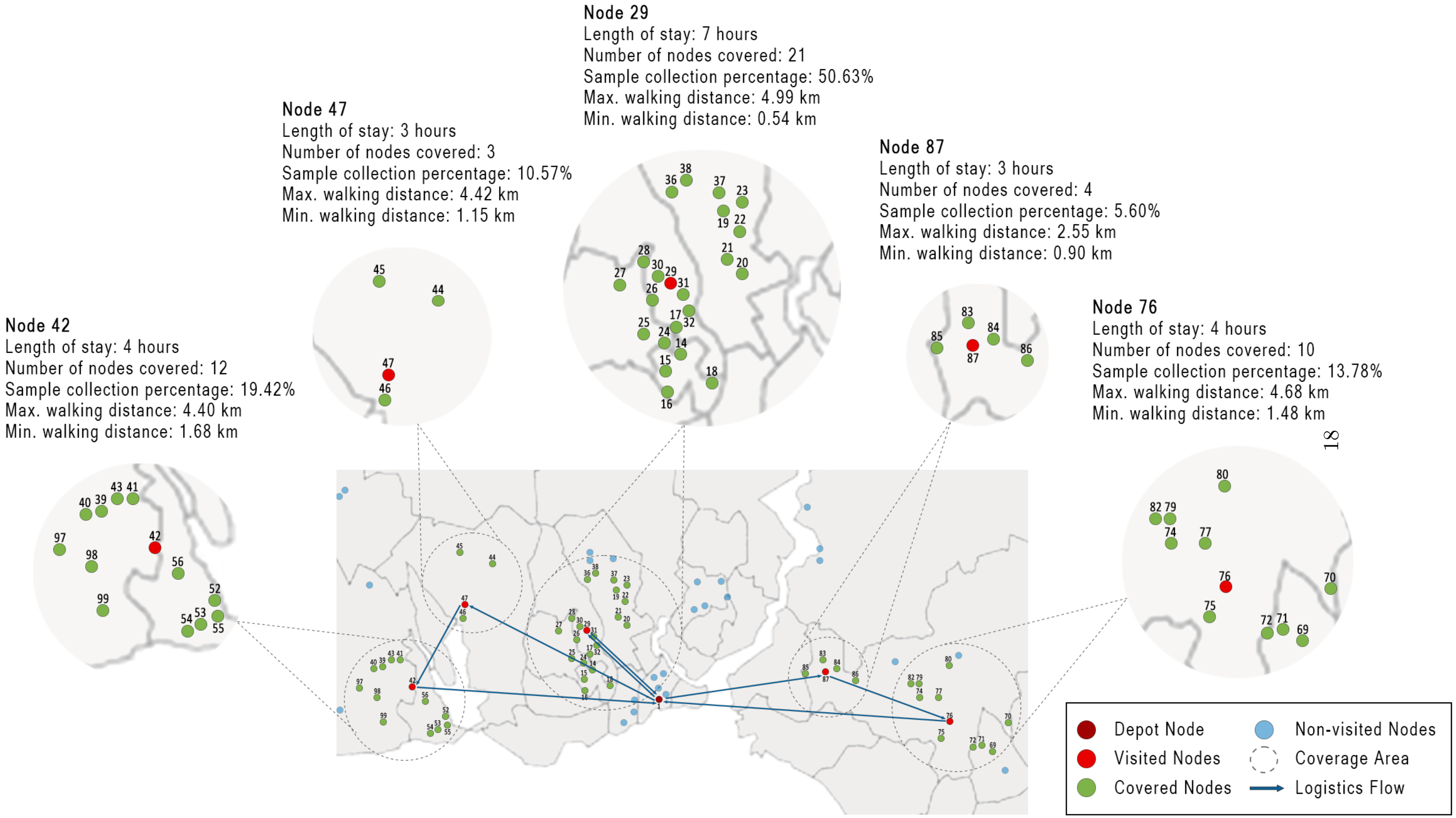


Figure 5: The Solution for Istanbul Case for the Maximization of Total Sample Collection

4.2. Minimization of Maximum Walking Distance

In this version of the proposed problem, the primary performance measure is given as the maximization of the total sample collection. Additionally, after analyzing the total sample collection, another important performance measure is defined for analysis purposes. The maximum distance between a covered node and a visited node is added to the model as an objective. The second performance measure is known as 'walking distance', which can also be minimized. This performance measure is considered since the attendees from covered nodes are expected to visit the mobile facilities on their own, therefore, their willingness may affect the sample collection. The walking distance is considered and represented as follows:

$$\min \quad \max c_{ij} \times a_{ij} \times y_{ik} \tag{20}$$

subject to (2) – (19)

The objective (20) is to minimize the maximum distance between a covered node and a visited node; in other words, to minimize the maximum walking distance.

Similar to the Base Case analysis in the previous part, we use three temporary testing centers with $\alpha = 0.5$ and $\beta = 0.5$ to analyze both objectives.

The ϵ-constraint method is used to evaluate the objectives simultaneously without any prioritizing. The non-dominated points are found by iterating the model with the step size of 0.01 km. From the set of nondominated points, the two solutions with the optimal outcomes for each objective and CPU time of the iterations are given in Table 6 and Table 7.

		Objective	CPU Time (seconds)	Distance Traveled by The Centers (km)	Number of Visited Nodes	Number of Covered Nodes
Optimal Max Sample	Max Sample	224 (sample)	0.62 sec	84.38	5	16
	Min Max Walking Distance	4.87 (km)				
Optimal Min Walking Distance	Max Sample	70 (sample)	0.05 sec	72.44	3	2
	Min Max Walking Distance	2.87 (km)				

Table 6: The Nondominated Solutions of Seoul Case

		Objective	CPU Time (seconds)	Distance Traveled by The Centers (km)	Number of Visited Nodes	Number of Covered Nodes
Optimal Max Sample	Max Sample	552,507 (sample)	41.22 sec	112.01	5	50
	Min Max Walking Distance	4.99 (km)				
Optimal Min Max Walking Distance	Max Sample	58,391 (sample)	0.96 sec	278.79	3	0
	Min Max Walking Distance	0 (km)				

Table 7: The Nondominated Solutions of Istanbul Case

The solutions of Seoul and Istanbul cases with the optimal outcome for maximizing the total sample collection indicates five locations are visited by three vehicles. Two vehicles visit two nodes, whereas one vehicle chooses to stay in the decided location during the shift time for both of the cases. Mobility is encouraged because of two aspects. First, fulfilling the walking distance requirement is easier, being at a distance of 4.87 kilometers for the Seoul case and 4.99 kilometers for Istanbul at most. Second, the diminishing sample collection potentials make the first stops less profitable after a certain time. In total, 16 locations for Seoul and 50 locations for Istanbul are covered by the 5 visited points. Therefore, 21 out of 25 districts of Seoul and 55 out of 99 neighborhoods of Istanbul reach the mobile testing applications, representing 84% and 55.56% of the potential points respectively. The total distance traveled by the vehicles is 84.38 kilometers for the Seoul case and 112.01 km for the Istanbul case. The solutions of Seoul and Istanbul cases with the optimal outcome for minimizing the maximum distance between a covered and a visited node indicate three locations are visited by three vehicles. This implies that the vehicles spend the shift at the same location. Mobility is discouraged, as fulfilling the walking distance requirement is quite complex, sometimes impossible, compared to the solution with a maximum total sample collection. Only two locations fulfill the defined distance for the Seoul case, whereas there are no covered points for the Istanbul case. Due to the walking distance requirement, the sample collection and the number of reached points decrease. Two districts of Seoul and no neighborhoods of Istanbul are covered by three visited spots. Thus, the mobile testing applications reach 5 districts out of 25 of Seoul and 3 neighborhoods out of 99 of Istanbul, which is 20% and 3.03% of the potential points respectively.

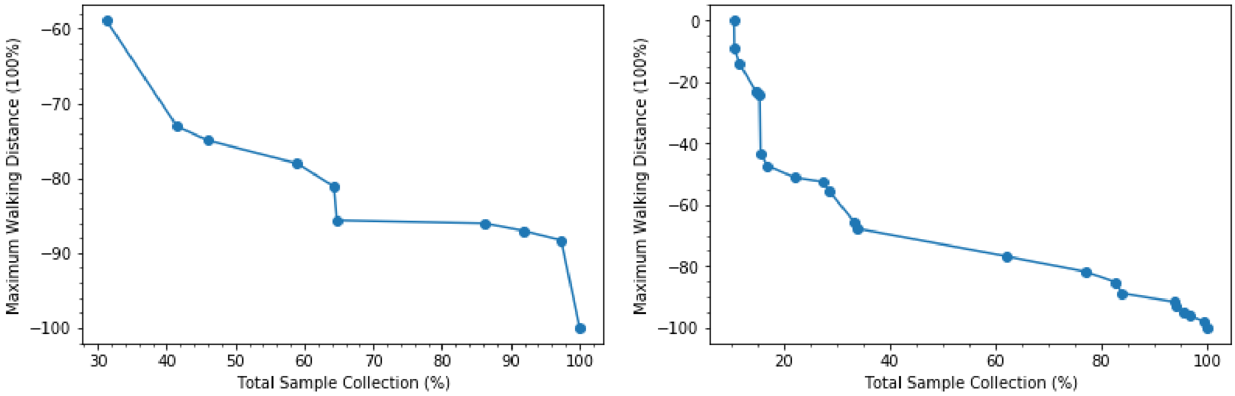
The total distance traveled by the vehicles is 72.44 kilometers for the Seoul case. The distance traveled does not differ significantly, whereas the sample collection difference is drastic. However, the total distance traveled by the vehicles is 278.79 kilometers for the Istanbul case, which is much longer than the optimal solution for the maximizing total sample collection. This implies the coverage requirement made the sample collection impossible by coverage that the traveled distance rose significantly to reach the populated nodes. One may observe the trade-off as increasing convenience, as being only a short distance away decreases the total sample collection of temporary testing centers. On the other hand, reducing the distance for the patients to be within walking distance may be an important concern for the decision-makers. Note that the travel distance may still be convenient, as the depot node is designated considering the centrality of the depot. Ensuring short travel distances of vehicles is beneficial, considering the traffic load and the transportation costs.

4.3. Pareto Analysis Between Two Objectives

We consider two objectives, precisely, maximizing the total sample collection and minimizing the maximum distance between a visited node and a covered node, in other words, minimizing the maximum walking distance. An analysis of the behaviors of the two objectives is necessary for the decision-makers to make conclusions analytically. For this purpose, the Pareto frontiers for the Seoul case and Istanbul case are shown in Figures 6a and 6b, respectively. The maximum distance values are multiplied with -1 in the graph to comply with the maximization setting of the first objective.

In Figure 6a, the increase in the maximum walking distance is close to the decrease in the total sample collection, in the range of 30-40%. Then, it is observed that the total sample collection increases sharply in the range of 65-90% with a small increment of the maximum walking distance. In contrast, the total sample collection increases slightly in the range of 95-100% with a significant increase in the maximum walking distance.

Further, we analyze 95-100% range of total sample collection in detail, represent the solution in Figure 7 and compared it with the base case. We have already analyzed the base case for Seoul in detail in Figure 4. When we enforce slightly more 10% less of maximum walking distance, we obtain a solution with 11.7% decrements in the walking distance. In addition, a considerably small loss of total sample collection occurs with about 3% while having common routing decisions with the base case. In this case, the schedule of two out of the three vehicles remain the same. The first vehicle again only visits node 6 and returns to the depot, and the second vehicle visits nodes 10 and 14 before returning to the depot. However, the third vehicle visits nodes 1 and 17, while in the base case, it visits nodes 2 and 18. The total sample collection decreases from 224 to 217 samples, since the sample collected by the third vehicle decreases from 67 to 60 samples.



(a) Seoul Case

(b) Istanbul Case

Figure 6: The Pareto Frontiers

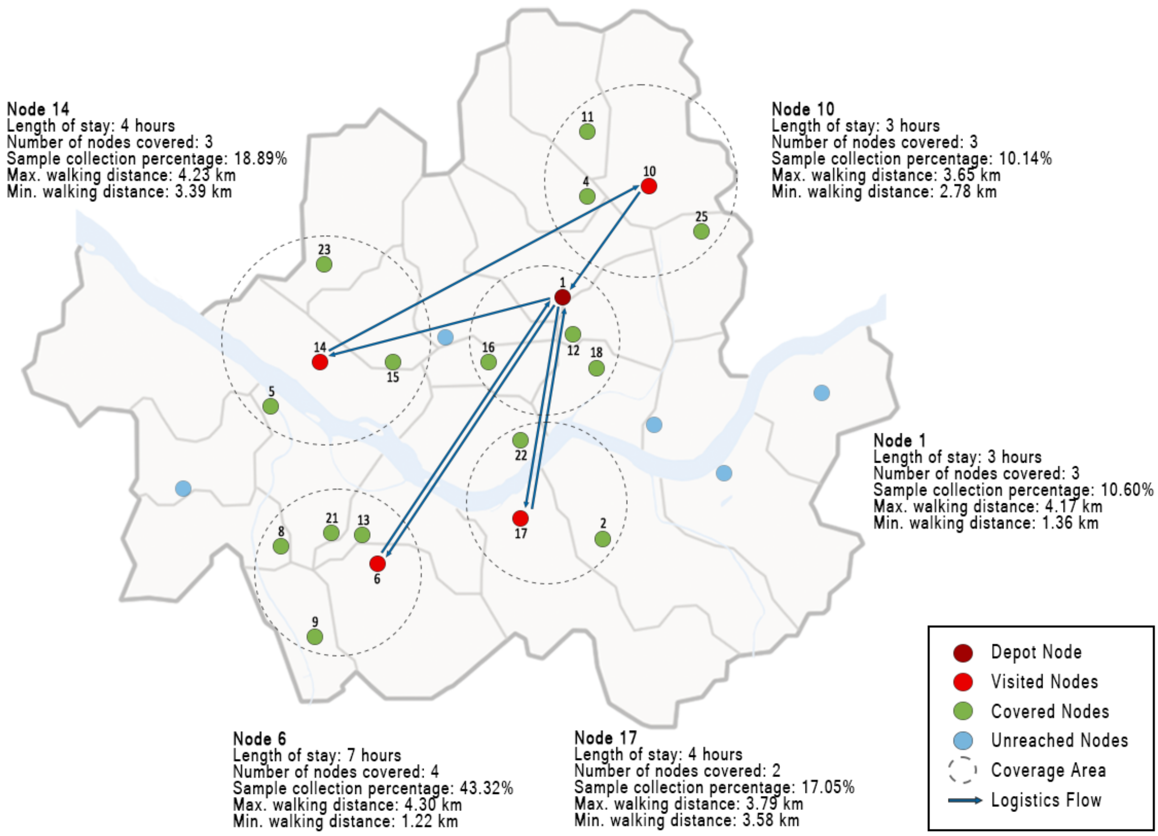


Figure 7: The Solution for Seoul Case with 10 percent less of maximum walking distance

In addition, one may note that node 1, which denotes the central hospital, is covered by node 18 in the solution for the base case. On the other hand, when 10 percent less of the maximum walking distance is enforced, node 1 is visited directly by a vehicle. In that case, the vehicle stays at the central hospital for 3 hours. In addition, node 17 is covered by node 2 in the optimal solution, whereas with 10 percent less of maximum walking distance, node 17 is visited directly by a vehicle, staying 4 hours. Furthermore, in the optimal solution, nodes 1, 7, 12, 16, 17, and 22 are covered during stay-overs at nodes 2 and 18. Similarly, with a 10 percent decrement in walking distance, nodes 2, 12, 16, 18, and 22 are covered during stay-overs at nodes 1 and 17. Nodes 2 and 18 have higher sample potential than nodes 1 and 17; however, the model chooses nodes 1 and 17 when the walking distance is decreased. When walking distance is decreased, to increase total sample collection. The reason is that the nodes with high sample potentials within the enforced radius such as 12, 16 and 22 are covered by visiting nodes 1 and 17. However, node 7 cannot covered in the solution with a 10 percent decrement in walking distance. The total number of nodes covered by the third vehicle decreases by one.

In Figure 6b, the total sample collection increases slightly in the range of 0-30% with a significant increase in the maximum walking distance, which implies giving up on the convenience by being in the short distance may not be worthwhile. In contrast, steadily significant increases in total sample collection are observed in the range of 30-80% with small increments of the maximum walking distance. The total sample collection increases in the range of 80-100% are relatively minor, while observing small increments of the maximum walking distance.

Moreover, we analyzed some points in the Pareto frontiers in detail and compared them with the base case with Istanbul data. We have already analyzed the base case for Istanbul in detail in Figure 5. In the optimal solution for Istanbul instance, a vehicle chooses to visit node 29 and stay for 7 hours. If we enforce a 1.8% reduction in walking distance, a vehicle visits node 28 rather than node 29, having all other visited nodes as the same. A slight decrease occurs in total sample collection with 0.46%. It can be recognized that if a vehicle visits node 28, there is a 0.9 km decrease in maximum walking distance with a tolerable loss in the percentage of sample collection. Furthermore, if we enforce a 4% reduction in maximum walking distance, the vehicle visits node 30 rather than node 28 or 29. In addition to the prior case, all other nodes visited are the same as the optimal solution except for node 30, and the percentage of sample collection decreases by 3.13%. When we further enforce changes in walking distance such as 5.21%, 7.01%, and 8.42%, we observe 4.50%, 5.86%, and 6.14% decrements in the sample collection, respectively.

We represent the solution for 8.42% decrements of walking distance in Figure 8. When compared with the optimal solution, the total sample collected decreases from 522,507 to 518,581 samples, while the walking distance changed from 4.99 km to 4.57 km. In the optimal solution for the Istanbul case, the vehicles visit nodes 29, 42, 47, 76, and 87, while with 8.42% decrements of walking distance, vehicles visit nodes 17, 35, 45, and 98. The number of nodes visited is decreased, as well as the number of nodes covered. In the optimal solution, 50 nodes are covered, while with 8.42% decrements of walking distance, there are only 34 nodes covered. In the optimal solution, one of the routes collects 50.63% of the total samples, and this extensive amount is collected by visiting node 29 and covering the nodes within the 4.99 km radius of that node. When we enforce 8.42% decrements in walking distance, the highest sample collected by one vehicle is found as 38.42%. When we compare those solutions, it is recognized that nodes 87 and 76 are visited in optimal solution; but neither visited nor covered in the solution for 8.42% decrements of walking distance. Similarly, node 35 is neither visited nor covered in the optimal solution, while it is one of the visited locations in solution for 8.42% change of walking distance.

It can be observed in both Seoul and Istanbul cases, with approximately 10% change in the walking distance, the total sample collected is affected slightly. The decision-makers can evaluate these minor changes in order to settle for a judgment.

These two figures, Figures 6a and 6b, show that if decision-makers decide to settle for approximately 15-25 percent less of the maximum walking distance, they can lose a significant amount of people in the associated total sample collection metric. There is a steeper decrease in the Seoul case since the depot in the Seoul case is close to many nodes with a high sample potential. However, nodes with a high sample potential may be scattered away from the depot in the Istanbul case.

4.4. Sensitivity Analysis on Problem Parameters

In the case of widely implementing the mobile application, the decision-makers may want to observe the results when the number of vehicles changes. Therefore, the analyses for the Seoul case are conducted for

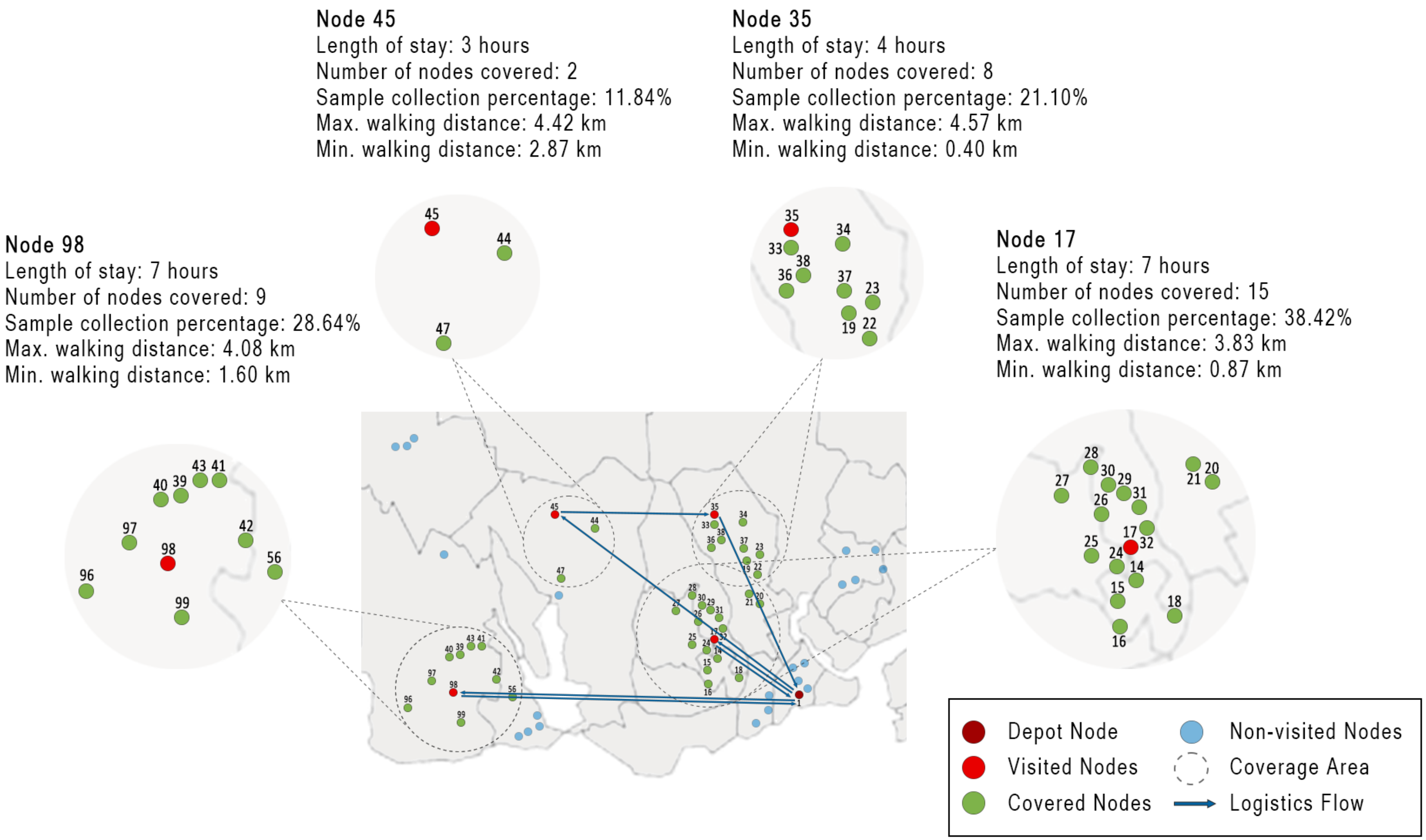


Figure 8: The Solution for Istanbul Case with 8.42 percent less of maximum walking distance

two, three, four, and five temporary sample collection centers as shown in Tables 8, 9 and 10.

The diminishing sample collection potential over time, in different levels, β is changed between 0 and 1 in increments of 0.1 for fixed α and T values. By changing the number of vehicles and the diminishing level of sample collection potential over time, the trend in the maximization of sample collection and the change in the mobility of the temporary testing centers can be seen. The total sample collection values, marginal increments of the sample collection, number of covered locations, and number of visited locations are shown in Table 8. Moreover, the diminishing sample collection potential due to coverage, in different levels, α is changed between 0 and 1 in increments of 0.1 for fixed β and T values. The trend in the maximization of sample collection and the change in the mobility of the temporary testing centers can be observed by changing the number of vehicles and the diminishing level of sample collection potential due to coverage. The results are demonstrated in Table 9. Finally, a sensitivity analysis is performed on time indicated to switch to the next part of the shift, T for fixed β and α values. The results are shown in Table 10. In the calculations, the maximum distance between a visited node and a covered node is observed as 5 kilometers, while not being restricted. When β increases, the sample collection potential remain closer to the initial level of the potential over time. Therefore, the sample collection increases. Note that when β increases, the difference between marginal increments appears stable. In this case, adding more testing centers is acceptable if the authorities seek to increase the availability of testing. When β is small, paying for more temporary testing centers is less reasonable due to the diminishing increments of sample collection.

Another aspect is that the mobility becomes disadvantageous when β increases, as the nodes with high sample potentials are likely to be still favorable even after some time. Therefore, the number of visited locations decreases. Note that the travel time is a period when testing cannot occur. Thus, traveling of the testing centers is not favored while the sample collection potential remains sufficiently large. Then, the tours and duration of each stay of the testing center are analyzed. Even if β is small, no testing centers visit more than two locations in the given period. It may explain the short runtimes, as there is a pattern regarding the diminishing potentials. There is an observed behavior of the testing centers when β is sufficiently small: Spending the first half on one spot, then traveling for the second half and staying there as long as the remaining time permits. If not, the testing centers remain as long as there is sufficient time to turn to the central hospital. Contrarily, it is not the case that the testing centers always stay at a node when β is large enough. When the β value is set to 1, the sample collection potential does not change over time. In this case, if more than three vehicles are used, then some testing centers visit more than one location.

The number of covered nodes appears not to be affected by β. The locations that cover the nearby points are highly likely to be chosen regardless of the level of potentials. The minimum number of covered nodes is 11, which is 44% of the nodes. This case is observed when β is larger than and equal to 0.8 with two temporary testing centers. Moreover, the maximum number of covered nodes is 17, which is 68% of the nodes, and it occurs when β is 0.3 and 0.4 with four and five temporary testing centers. Similarly, the maximum number of covered nodes is observed when β is 0.2 with four vehicles. Due to the limited number of testing centers, the number of visited locations is less than the covered locations. When β is 0.3 and the number of vehicles is 5, the testing centers reach every node by visiting and by being sufficiently close, even though full coverage is not guaranteed. When β is 0.8 and the number of vehicles is two, the worst case in terms of availability occurs; even then, 52% of the locations are provided with the testing service.

We will further analyze the effect of diminishing sample collection potential due to coverage, α, on the sample collection for fixed β and T values. As α increases, the sample collection potential of covered nodes gets closer to the level of the sample collection potential of the visited node. As a result, the sample collection increases. The decrement in α causes the difference between marginal increments to increase. The reason is that with a decrement in α, fewer samples will be collected from covered nodes. When α is small, paying for more testing centers is much more reasonable. It is because sample collection by visiting as many nodes as possible is much more beneficial than sample collection due to coverage.

Furthermore, the mobility becomes slightly disadvantageous as α increases. The reason is that the sample collection potentials of visited and covered nodes are getting equally favorable. Thus, the number of visited locations slightly decreases. When α is small, the testing centers do not visit more than two locations. As previously stated, it can be the reason for the short runtimes. Also, for α, it is observed that the vehicles spend the first half in one location, then travel for the second half and stay there for the remaining time.

β	Number of temporary testing centers (m)	Total Sample Collection	Marginal Increments of Sample Collection (Percent)	Number of Covered Nodes	Number of Visited Nodes	CPU of Total Sample Collection (Seconds)
0.1	2	166		13	4	0.45
	3	212	27.71	16	5	0.87
	4	242	45.78	16	8	7.28
	5	258	55.42	16	8	9.81
0.2	2	166		13	4	0.44
	3	212	27.71	16	6	0.85
	4	244	46.99	17	7	6.84
	5	266	60.24	16	8	12.85
0.3	2	166		13	4	0.46
	3	214	28.92	16	5	0.79
	4	250	50.60	17	7	1.92
	5	275	65.66	17	8	56.36
0.4	2	166		13	4	0.47
	3	219	31.93	16	5	0.59
	4	256	54.22	17	7	1.39
	5	285	71.69	17	7	12.65
0.5	2	171		12	3	0.35
	3	224	30.99	16	5	0.53
	4	264	54.39	16	5	1.30
	5	296	73.10	16	7	2.94
0.6	2	176		12	3	0.31
	3	229	30.11	16	5	0.46
	4	275	56.25	16	5	0.77
	5	310	76.14	16	5	1.45
0.7	2	182		12	3	0.27
	3	235	29.26	15	4	0.44
	4	286	58.51	16	5	0.80
	5	327	79.67	16	5	1.02
0.8	2	189		11	2	0.22
	3	244	29.26	15	4	0.40
	4	298	58.51	16	5	0.40
	5	343	82.45	16	5	0.79
0.9	2	197		11	2	0.24
	3	254	28.93	12	3	0.36
	4	309	56.85	13	4	0.38
	5	359	82.23	16	5	0.60
1	2	206		11	2	0.24
	3	266	29.13	12	3	0.31
	4	323	56.80	13	4	0.62
	5	375	82.04	16	5	0.74

Table 8: Sensitivity Analysis Results of Problem Parameter β

More interestingly, this pattern does not change when α is large enough. When the α value is set to 1, the sample collection potential does not change due to coverage. Therefore, a more favorable strategy is visiting districts that can cover other districts with high sample collection potential.

As expected, the value of α seems to affect the number of nodes covered. The number of visited nodes decreases slightly, but the number of covered increases significantly as α increases. Since α affects the sample collection from the covered nodes, the visited locations are highly selected due to their coverage of nearby

α	Number of temporary testing centers (m)	Total Sample Collection	Marginal Increments of Sample Collection (Percent)	Number of Covered Nodes	Number of Visited Nodes	CPU of Total Sample Collection (Seconds)
0.1	2	101		6	3	0.52
	3	136	34.65	11	5	0.42
	4	168	66.33	14	7	0.97
	5	191	89.10	14	7	10.27
0.2	2	114		13	4	0.27
	3	154	35.09	15	5	0.45
	4	189	65.79	14	7	1.07
	5	214	87.72	14	7	7.64
0.3	2	131		13	4	0.37
	3	176	34.35	15	5	0.53
	4	210	60.31	15	7	1.47
	5	238	81.68	16	7	6.21
0.4	2	149		11	3	0.37
	3	200	34.23	16	5	0.53
	4	235	57.72	16	6	1.51
	5	267	79.19	16	7	2.36
0.5	2	171		12	3	0.35
	3	224	30.99	16	5	0.53
	4	264	54.39	16	5	1.33
	5	296	73.10	16	7	2.84
0.6	2	194		12	3	0.32
	3	249	28.35	16	5	0.65
	4	295	52.06	17	6	1.04
	5	328	69.07	16	7	2.64
0.7	2	217		12	3	0.37
	3	275	26.73	16	5	0.49
	4	327	50.69	16	5	1.00
	5	361	66.36	17	4	1.63
0.8	2	242		14	3	0.30
	3	305	26.03	15	4	0.51
	4	358	47.93	17	6	0.91
	5	395	63.22	17	6	1.86
0.9	2	266		14	3	0.30
	3	334	25.56	15	4	0.49
	4	390	46.61	17	6	0.90
	5	429	61.28	17	6	2.02
1	2	291		14	3	0.31
	3	367	26.12	15	4	0.53
	4	421	44.67	17	6	0.88
	5	462	58.76	17	6	1.43

Table 9: Sensitivity Analysis Results of Problem Parameter α

points. When α is 0.1 with two temporary testing centers, the minimum number of covered nodes occurs, and it is 6, which is 24% of nodes. Moreover, the maximum number of covered nodes is observed when α is 0.6 with four temporary testing centers, and α is greater than and equal to 0.8 with four and five temporary testing centers. The maximum number of covered nodes is 17, which is 68% of the nodes. When α is 0.1, and the number of vehicles is 2, the worst case in terms of availability occurs. In this case, only 36% of the locations are provided with the testing services. Moreover, when α is 0.8, and the number of vehicles is 4 and 5, the best case in terms of availability occurs. In this case, 92% of the locations are provided with the testing services. Also, this availability level is reached when α is 0.9 and 1 with 4 and 5 vehicles.

T	Number of temporary testing centers (m)	Total Sample Collection	Marginal Increments of Sample Collection (Percent)	Number of Covered Nodes	Number of Visited Nodes	CPU of Total Sample Collection (Seconds)
1	2	124		16	5	0.51
	3	158	27.42	17	6	0.79
	4	188	51.61	16	5	0.83
	5	215	73.39	16	6	1.14
2	2	144		16	5	0.32
	3	183	27.08	17	6	0.73
	4	215	49.31	17	7	1.04
	5	242	68.05	16	6	1.74
3	2	158		15	4	0.32
	3	205	29.75	16	5	0.64
	4	241	52.53	17	6	1.40
	5	270	70.89	16	7	1.84
4	2	171		12	3	0.35
	3	224	30.99	16	5	0.53
	4	264	54.39	16	5	1.30
	5	296	73.10	16	7	2.95
5	2	183		12	3	0.31
	3	238	30.05	16	5	0.57
	4	283	54.64	16	5	1.02
	5	322	75.96	16	6	2.45
6	2	194		12	3	0.28
	3	252	29.99	16	5	0.38
	4	303	56.19	16	5	0.91
	5	348	79.38	14	6	1.53
7	2	206		11	2	0.35
	3	266	29.13	12	3	0.33
	4	323	56.80	13	4	0.46
	5	375	82.03	16	5	0.86

Table 10: Sensitivity Analysis Results of Problem Parameter T

Finally, we analyze the effect of T on the sample collection. As T increases, the first part of the shift increases, and the second part decreases. It results in an increment in sample collection. Also, the difference between marginal increments appears to increase. In order to increase the availability of testing, paying for more test centers is again acceptable.

When T increases, mobility becomes disadvantageous. The reason is that the locations with high sample collection potential are likely to be still favorable in the first part of the shift. Rather than moving to another location, staying in the currently visited location is more favorable. Therefore, there exists a decrease in the number of visited locations. Furthermore, the same pattern from previous analyses is observed when we analyze the tours and durations of the vehicles. A vehicle does not stay in more than two locations on tour. As T increases, the same pattern is observed. When T is set to 7, the sample collection potential of points does not change over time. The rest of the time is used for traveling from the depot and returning to the depot.

In addition, the number of covered nodes is affected by T. As T increases, the number of covered nodes appears to decrease. The underlying reason is that even though the vehicles do not cover many locations, it is enough to visit and cover locations with high sample collection potential. When a node is covered, the sample collection potential of that node decreases due to coverage. However, as T increases, the sample collection potential over time becomes less critical. The minimum number of covered nodes is 11, and the maximum number is 17, which represents 48% and 68% of the locations, respectively. The minimum number of covered nodes is observed when T is 7 with two temporary testing centers. Moreover, the maximum number of covered nodes is observed when T is 1 with three temporary testing centers, and T is 2 and 3 with four temporary testing centers. When T is 2, and the number of vehicles is 4, the testing centers provide testing service to every node by visiting or covering. Similar to the analysis in β, this case occurs even though full coverage is not guaranteed. When T is 7, and the number of vehicles is 2, the worst case in terms of availability occurs. 52% of the locations are provided with the testing service. It can be noticed that similar observations done for β are observed for also T since they both affect the sample collection potential of nodes due to time. However, it can be noticed that T also affects the importance of β. As T increases, the second part of the shift becomes less critical, and nodes' sample collection potential remains high for a long time. Therefore, rather than moving to another location, staying in a location longer is more beneficial in terms of sample collection.

To conclude, the sample collection level, time of shift change, and the number of testing centers affect the total sample collection. As β increases, the sample collection potential decreases less, and the marginal increments of the sample collection are higher, which justifies having more vehicles for testing. The proportion of locations reached is more than half in the calculations. This indicates that even with fewer vehicles, the availability of testing may be at an acceptable level. Moreover, when α decreases, the sample collection potential of covered nodes decreases significantly. Then the marginal increments of the sample collection get higher, and it also justifies having more vehicles for testing. The parameters α and β similarly affect the marginal sample collection when α is getting smaller and β is getting larger. Furthermore, T has a similar effect on the total sample collection as β. As T increases, the sample collection potential in the first half of the shift does not decrease, and the marginal increments of the sample collection get higher values. Due to this fact, T seems to affect the importance of the parameter β since β represents the diminishing sample collection potential of nodes in the second part of the shift. According to the analysis, the decision-makers need to determine the number of testing centers, considering the cost of constructing testing centers and the importance of the testing service.

5. Two-stage Math-heuristic Approaches

According to COVID-19 cases, our problem may be applied in a more extensive network to reach a larger part of the community. Due to typical vehicle routing constraints, the increase in potential points leads to an extensive underlying network. Hence, the computational times can significantly be long for large instances with many potential locations. Long computational times may not be preferable with the aim of responding quickly to the emerging need for testing. Therefore, we designed four two-stage heuristic approaches yielding satisfactory solutions with small optimality gaps in shorter computational times and compared optimality gaps. The proposed two-stage heuristics can be stated generally in two steps as depicted in Table 11.

The general description of the two-stage heuristic approaches is given, and accordingly, we introduce four heuristic approaches based on the differences in Step 1, which is named as *NodeSelection*. Those four heuristics are *Random*, *NodePotential*, *SetCovering*, and *CoECNodePotential* Heuristics. The *NodeSelection* Step of each heuristic is explained in detail.

- ***NodeSelection* for *Random* Heuristic**
  NodeSelection for *Random* Heuristic aims to find a subset of nodes to visit randomly. Random node selection was utilized to observe the effortless selection of a subset of nodes to visit. In this heuristic, 25 random nodes, including the depot node 1, are selected in this step. Then, utilize selected nodes in step 2.

Table 11: General Two-Sage Heuristic Approach

General Two-Stage Heuristic Approach	
Step 1: (*NodeSelection*)	Develop a strategy to find a subset of nodes to visit with a pre-determined number of nodes. This step can be called as *NodeSelection* step in further description.
Step 2:	Feed the nodes that are obtained in ***NodeSelection*** **Step (Step 1)** into the main model in Section 3 with minor adjustments. First, the set of possible visit locations and the set of nodes that those possible locations can cover are adjusted. The set of nodes where the vehicles can be located is determined by the subset obtained from ***NodeSelection*** **Step (Step 1)**. The original set of nodes can be still available for coverage by visiting the nodes in the subset. The description implies that the visiting decisions are made from a smaller set while preserving the coverage characteristics of the main model.

- ***NodeSelection*** **for** ***NodePotential*** **Heuristic**
  NodeSelection for *NodePotential* Heuristic aims to find a subset of nodes to visit according to the sample collection potentials of each node. Rather than cumulative sample collection potential, including sample collection potentials of coverages, only the sample collection potentials at each node are sorted from highest to lowest. After sorting the nodes, the depot node 1 is included, then, the nodes with the highest potentials are selected until reaching 25 nodes. Then, proceed to step 2 with the selected nodes.

- ***NodeSelection*** **for** ***SetCovering*** **Heuristic**
  As the first step in *SetCovering* Heuristic, the aim is to find a subset of nodes to reach all the locations in the network, either by being sufficiently close or visiting. For this purpose a set covering model is proposed. Solve the following mathematical model *(SetCovering)*. Note that parameter a_{ij} is as defined in the Section 3. Decision variable:

$$y_i = \begin{cases} 1 & \text{if location } i \in N \text{ is in the subset} \\ & \text{of possible visit locations} \\ 0 & \text{otherwise} \end{cases}$$

SetCovering:

$$\min \quad \sum_{i \in N} y_i \tag{21}$$

subject to

$$\sum_{i \in N} a_{ij} \times y_i \geq 1 \quad \forall j \in N \tag{22}$$

$$y_i \in \{0, 1\} \quad \forall i \in N \tag{23}$$

This mathematical model finds the minimal subset of nodes to reach all the locations in the network, either by being sufficiently close or visiting. Constraints (22) ensure every node is receiving the temporary testing service at least one way, either by being covered by another location within a predefined distance or by being visited. Constraints (23) give the binary restrictions on the decision variables. The objective function leads to finding the minimum number of nodes to access every node in the network. After selecting nodes via *SetCovering* model and including depot node 1, proceed to step 2.

- ***NodeSelection*** **for** ***CoECNodePotential*** **Heuristic**
  NodeSelection for *CoECNodePotential* Heuristic aims to find a subset of nodes to visit according to the cumulative sample collection potentials of each node. The cumulative sample collection potential includes the sample collection potentials at each node and the sample collection potentials of coverages.

Each node's cumulative sample collection potentials are sorted from highest to lowest. After sorting nodes, the highest node is selected, and the a_{ij} matrix is analyzed. The nodes within the coverage radii of these nodes are eliminated from the sorted list. Then the next highest node is selected, and the nodes within the coverage of this node are also eliminated. Accordingly, after including depot node 1, the highest potential nodes are selected while their coverage radii are eliminated until reaching 25 nodes. The algorithm that is used for the procedure is given in Algorithm 1. The abbreviation *CoECNodePotential* stands for "Coverage Eliminated Cumulative Node Potentials," which represents the process of the heuristic. Then, proceed to step 2 with the selected nodes.

Algorithm 1: Algorithm for *NodeSelection* for *CoECNodePotential* Heuristic

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Calculate the cumulative sample collection potential of each node in the set of possible locations for testing temporary centers (N).

$$b_i^{'} = b_i + \sum_{j \neq i \in N} \alpha \times b_j \times a_{ij}$$

where $b_i^{'}$ denotes the cumulative sample collection potential of each node in set N.

Sort the nodes from highest to lowest according to their $b_i^{'}$ values.

$N^{'}$ denotes the list of nodes sorted from highest to lowest.

Define a set V denoting the subset of nodes selected to visit and $V = \{1\}$ where node 1 denotes the depot.

while $|V| \leq 25$ **do**

  Pick the node with the highest $b_i^{'}$ in the list $N^{'}$.

   Denote this node as i^*

   $V = V \cup \{i^*\}$;

  Check the coverage radius of the selected node (i^*).

   for $j \in N^{'}$ **do**

    if $a_{i^*j} = 1$ **then**

     $N^{'} = N^{'} \backslash \{j\}$

Regarding the heuristics proposed, each heuristic's objective values are compared with the optimal objective values in Table 12. All heuristics solve the problem in a matter of seconds. However, when the number of vehicles is given as five for *SetCovering* Heuristic, the CPU time of the heuristic is observed to be 169.27 seconds. Therefore, compared to other heuristics, the CPU for *SetCovering* Heuristic is slightly longer.

Number of Vehicles	Optimal Objective Value	Objective Value for *Random* Heuristic	Gap (%)	Objective Value for *NodePotential* Heuristic	Gap (%)	Objective Value for *SetCovering* Heuristic	Gap (%)	Objective Value for *CoECNode-Potential* Heuristic	Gap (%)
2	445,457	395,352	11.25	438,068	1.66	404,367	9.22	429,803	3,51
3	552,507	486,314	11,98	540,464	2.18	499,127	9.66	549,693	0.51
4	652,545	561,5788	13,94	617,797	5,32	585,156	10,33	646,977	0,85
5	726,938	619,3494	14,80	694,736	4,43	653,561	10,09	717,019	1,36

Table 12: Objective Value Comparison for Heuristic algorithms for Istanbul, Turkey

For *Random* Heuristic, the given objective values are observed by taking the average of five runs. Analyzing *Random* Heuristic aims to observe an effortless and intuitive way of selecting a subset to visit. Even though the results are not as good as *NodePotential* and *CECNodePotential* Heuristics, the results are close to *SetCovering* Heuristic.

SetCovering Heuristic aims to observe a subset of nodes covering all other nodes. If the locations selected from the subset determined by SetCovering Heuristics have high potentials either by visiting or covering, then the total sample collection is expected to be high. However, the results are only slightly better than *Random* Heuristic. For *SetCovering* Heuristic, the optimality gaps are better than *Random* Heuristic. The gaps for *Random* Heuristic are 11.25%, 11.98%, 13.94%, and 14.80% with the increasing vehicle number. With those gaps, *Random* Heuristic cannot surpass *SetCovering* Heuristic in any case. The gaps for both heuristics are close and comparable. However, the results imply that *SetCovering* Heuristic outperforms the *Random* Heuristic with slightly fewer gaps in any number of vehicles. *SetCovering* Heuristic finds a subset of nodes that can cover all nodes; however, the gaps are slightly better than the *Random* Heuristic. The underlying reason would be based on the fact that the *SetCovering* Heuristic does not consider the sample collection potentials of the locations, but solely an assurance to serve all the locations in the set. The nodes that are not included in the visiting subset and expected to be covered may have high sample potentials. Even if those nodes are reached by a visited location in the subset, the sample collection potential loss is significant due to diminishing sample collection potentials by coverage, represented by α. Likewise, the visiting subset may contain lower sample collection potentials, affecting the objective value. Therefore, *SetCovering* Heuristic is not performing outstanding as expected.

The approach in *NodePotential* Heuristic includes the sample potentials for each node, implying that it is a closer approach to the approach in the main model. On the other hand, in the *SetCovering* Heuristic, the approach is based on an obligation to serve every node. It aims to cover every node with a minimum number of visited nodes, rather than considering the sample collection potentials. In that perspective, the approaches used in heuristics separate them in terms of the results. In addition, since *NodePotential* and *CoECNodePotential* Heuristics highlight focuses on nodes with high sample potentials or cumulative sample potentials, we observe better results with those heuristics. For *SetCovering* Heuristic, the optimality gaps are worse than both *NodePotential* and *CoECNodePotential* Heuristics, and gaps are very distinct. The gaps for *SetCovering* Heuristic are 9.22%, 9.66%, 10.33%, and 10.09% with the increasing vehicle number. *SetCovering* Heuristic falls behind both *NodePotential* and *CoECNodePotential* Heuristic in any case with a significant difference in gaps.

The approaches in *NodePotential* and *SetCovering* Heuristics are combined to design the approach in *CoECNodePotential* Heuristic. This approach considers the high sample collection and coverage radius of the visited node by selecting the nodes with high sample potentials and eliminating the nodes within the coverage radius of the selected nodes. This approach is better than SetCoverage and *NodePotential* Heuristics since it selects a subset of nodes considering both coverage and cumulative sample potentials of the locations. In *NodePotential* and SetCoverage Heuristics, the constructed subsets do not focus on coverage or sample potentials at the same time. Therefore, the subset selection might include nodes within multiple coverage radii or nodes with low sample collection potentials. Since the primary purpose is to increase the total sample collection, *NodePotential* and *CoECNodePotential* Heuristic find proper subsets of nodes, yielding closer results to the optimal. Significantly, the subset of *CoECNodePotential* includes the nodes that fit both the constraints and objective function of the main model. In that perspective, *CoECNodePotential* Heuristic has the closest approach to the main model. The gaps for *NodePotential* Heuristic are 1.66%, 2.18%, 5.32%, and 4.43% with the increasing vehicle number. *NodePotential* Heuristic falls behind *CoECNodePotential* Heuristic in almost all cases. Only in the case with two vehicles, the *NodePotential* Heuristic surpasses the *CoECNodePotential* Heuristic.

The optimal solutions can be obtained within seconds for small network problems, and a heuristic approach may not be critical. However, optimum solutions may not be as smoothly attainable for the more extensive networks. For the instances solved, the solution quality of *NodePotential* and *CoECNodePotential* Heuristics are outstanding. The gap of *CoECNodePotential* Heuristic is getting smaller than gap of *NodePotential* as the number of vehicles increases. Therefore, *NodePotential* heuristic can be preferred with fewer vehicle cases, while *CoECNodePotential* Heuristic can be preferred for cases with more vehicles.

6. Conclusion

In this study, we addressed the current global issue of responding to the COVID-19 outbreak due to the high contagion and severity of the disease. We believe we are the first to study the logistics of temporary testing centers to increase sample collection for PCR testing during the pandemic. We also aim to establish an exemplary mobile testing system to increase the accessibility and availability of testing at the beginning of pandemics by compiling the testing strategies. We conducted interviews with individuals in the field from Turkey, South Korea, and the UK to understand the current testing system dynamics. As a result, the temporary testing centers appear to be a successful means of increasing the availability and convenience of viral testing. In this study, we proposed a generic and easy-to-implement mobile sample collection system based on the best practices in the UK and South Korea. Then, we used the model to implement mobile testing strategies in Turkey through a case study.

Currently, authorities have developed various strategies against the current state of the pandemic; however, the pandemic is ongoing. Furthermore, there are dangerous variants of the virus that can lead to other outbreaks in the future. Our study will be helpful for such a pandemic process via proposing imitable and paradigmatic work on a mobile testing system that can be used in real-life. In addition, for Turkey, we offer the testing centers as a part of contact tracing to access the disadvantaged communities in addition to the other implementations of mobile testing. The proposed system has equipped testing vehicles with health personnel to conduct the sample collections of the patients. Therefore, the false-negative results caused by improper collection are less likely. Moreover, all testing vehicles are affiliated with the central laboratory, which provides more control over the testing process.

First, a mathematical model was developed to maximize the total sample collection. This model decides on the locations and duration of the stay of vehicles, as well as the tours of temporary testing centers. Later, we introduced another performance measure to analyze the willingness of attendees from the covered nodes to provide a sample for a given network and a given set of parameters. The optimal solutions for the Seoul and the Istanbul instances are found based on both performance measures. The Pareto efficient frontiers of both cities suggest that if the decision-maker opts to settle for approximately 15-25 percent less of the maximum walking distance, they can lose a significant amount of people regarding the total sample collection.

Furthermore, the sensitivity analyses for the problem parameter, α, β and T are conducted. Firstly, an analysis on the diminishing level of the sample potential parameter β and the number of vehicles is conducted. Based on the results, one can observe that the number of temporary testing centers does not affect the number of locations covered. However, an increasing number of testing centers provides the opportunity to visit fewer locations per vehicle, and increasing β levels discourage the vehicles from moving to other locations. Therefore, decision-makers may decide on the number of vehicles considering the construction cost of the temporary testing centers and the sample collection potentials of a location over time. A significant number of locations are covered with even just a few vehicles. Later, a sensitivity analysis on the diminishing level of the sample potential parameter α and the number of vehicles is conducted. Based on the results, the number of temporary testing centers affects the locations covered since α represents the change in sample collection potential of covered nodes. Moreover, as α increases, vehicles are discouraged from moving to other locations. It is since the sample collection potential of covered nodes will be higher, and total sample collection will increase. Finally, the effect of parameter T on total sample collection is analyzed. As T increases, the total number of covered and visited nodes appears to decrease. Also, increasing T discourages mobility since diminishing sample collection potential over time will have a less critical impact on the total sample collection. The authorities may increase α, β, and T by announcing the testing center visits via the Internet or local news.

The computational performance of the exact method proposed was not as satisfactory in larger problems; then, we also designed more efficient math heuristic algorithms. The primary purpose behind these two-stage algorithms was to develop strategies to find location decisions and feed them to the main mathematical model. Two of those heuristic approaches significantly decreased computational times while providing close to optimal solutions in our experiments.

To the best of our knowledge, there is no OR study that focuses on a mobile sample collection system, considering demand depending on both time and coverage aspects. Even though this study proposes a novel approach, there are some limitations, and thus various extensions can be considered. The current model is constructed as deterministic, and in real-life, a decision maker can encounter uncertainties such as uncertainties in travel time. Many factors, such as weather and traffic conditions, may impact travel time. The uncertainty in travel times may impact the number of temporary testing centers required to provide a testing service, the routes, and the duration of stays of temporary testing centers and thus can be a fruitful future research area.

In our problem, the sample collection potential of the district diminishes depending on the length of stay. However, the sample collection potential can vary depending on the time the vehicle arrives at the district. For instance, the sample collection potential during the morning shift can be less than during the afternoon shift. We have utilized a 2-step function to represent diminishing sample collection. In order to illustrate the gradual coverage depending on the time of arrival, other forms of gradual decay functions can be constructed. Further, analyzing the available data for hourly sample collections could lead to other types of functions. A different form of gradual decay functions may impact the visits' duration, directly affecting the total sample collection. Moreover, the sample collection potentials are considered parameters in our problem. However, they can deviate since the number of people who would like to provide samples can vary due to many conditions, such as availability and willingness. Such uncertainty in sample collection potential can lead to different problems and models which deem to study.

Furthermore, the planning horizon for our problem customarily is chosen as one day. In practice, the sample collection is not a one-day occasion but a procedure repeated in successive periods and thus a more extended horizon problem can be analyzed as a future extension.

Finally, the sole boundary in our problem is the time restriction for a vehicle to complete their shifts. The vehicles are assumed to have no physical capacity boundary. However, the number of samples that can be evaluated during a day without spoilage can be an essential restriction. Since PCR testing is expensive and unavailable in some hospitals, evaluating each sample collected within the day may not be possible. Therefore, the hospitals and labs may consider limiting the number of samples to evaluate due to technical and personnel constraints. This limitation would directly affect the sample collection by temporary testing centers since the collected samples are evaluated in the labs at the end of the collection activity. Thus, boundaries on vehicle capacity can be considered a future research area.

Other possible alternative application areas for the proposed model can also be investigated as a future direction. For instance, carrying and serving vaccination for COVID-19 to mobile healthcare facilities can be one of those extensions. There might be new restrictions due to the supply-chain properties of vaccination; however, accessibility and availability for vaccination should be considered due to the current pandemic. Furthermore, improving the existing math heuristics or developing a meta-heuristic for the problem can be considered an extension. Due to coverage and time considerations, generating a feasible solution or covering neighborhoods is more complex than the classical Selective Vehicle Routing Problems. Finally, our approach to the problem is novel, so it can be a worthwhile avenue to perform polyhedral analysis and generate valid cuts for it as a further extension.

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