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A Vehicle Routing Problem with Time Windows and Workload Balancing for COVID-19 Testers: A Case Study

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Abstract: Due to the COVID-19 pandemic, laboratories have faced unprecedented demand for in-home delivery test services. This drastic demand increase requires a rapid reaction from laboratories to manage their testers in order to respond to the high demand volume and avoid unnecessary costs. This study provides an optimization model based on the vehicle routing problem with time windows by considering the testers' workload balancing to improve laboratories' assignment and routing policies. A medical lab that has faced this situation for its in-home test services is taken as a real-world case in the current study. A mixed-integer programming model is solved for small instances using the CPLEX solver, and an adaptive large neighborhood search algorithm is implemented for large instances. Ultimately, the obtained solutions are compared to the real-world implementation of the lab on a dataset of six consecutive days, and the results are further discussed.

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1. INTRODUCTION

The COVID-19 pandemic refers to the spread of the SARS-CoV-2 virus that started in the early 2020 and rapidly became a significant concern for all countries worldwide. According to the World Health Organization, more than 288 million infected cases and more than 5.4 million deaths have been reported until January 2022 (WHO, 2022). This pandemic created numerous challenges for many organizations, especially medical centers and healthcare service providers. Preventive policies such as quarantine and lock-down that governments had to take to control the disease caused the most severe depression since 1930, and reports show that the global GDP has reduced between 2.9% and 2.4% in 2020 (Gupta et al., 2020).

The preventive policies increased the demand for home delivery services and made them more popular than ever, providing an extraordinary opportunity for online retailers to improve their market share. On the other hand, some organizations were unprepared to offer home delivery services to their customers on a large scale, so managing their resources became a significant challenge. Medical laboratories are one of those organizations that had a limited number of in-home test deliveries before the pandemic; however, their demand for home COVID-19 tests (i.e., PCR tests) abruptly increased. Patients can receive the service in their home by paying an extra transportation fee if they prefer to avoid going to laboratories to reduce the

risk of getting infected or if they have to take in-home tests due to the regulations. Therefore, the demand exceeds the laboratories' capacities for home services, and there is a need for these service providers to manage their resources efficiently to meet their demand.

The idea of the home delivery tests is connected to the home health care (HHC) services literature. There are several benefits in receiving HHC, including reduced hospital demand and bed occupations that may allow hospitals to serve more patients. In addition, the provided treatment procedure by the HHC companies are more customized and specialized due to their ability to focus on particular patients' needs (Cissé et al., 2017).

In 2011, around 4.7 million patients in the US received home-care services, and at that time, 12,200 HHC companies were operating in the US with around 143,600 caretakers (Fikar and Hirsch, 2017). HHC services are estimated to account for up to 5% of the health sector's total budget (Genet et al., 2012). In an HHC company, supply chain and transportation are critical activities necessary for delivering drugs and equipment to patients' locations, transporting caretakers or physicians to the predefined locations and returning them to the medical center. Another responsibility of this part of an HHC network is taking the biological samples from patients using professional nurses and transferring these tests to the laboratories for performing examinations (Liu et al., 2013). A survey in

Norway shows that, on average, transportation between patients and hospitals accounts for more than 20% of HHC caretakers' work shifts (Holm and Angelsen, 2014). For more details on the HHC literature, the reader is referred to a recent literature survey and bibliometric analysis by Di Mascolo et al. (2021).

A vehicle routing problem (VRP) can be used to minimize the transportation costs assuming a set of customers with known demands that must be satisfied by a supplier. Although reducing the transportation costs is usually the primary goal of VRP, other factors such as consistency, customer satisfaction, and resource balancing can also affect the quality of the solutions in practice (Matl et al., 2018). The literature on the VRP with workload balance is scarce despite the importance of the subject in practical situations. For instance, the workload balance of nurses who perform the in-home sample taking is essential not only to reduce the risk of them being affected but also to increase employee satisfaction. The former can be obtained by balancing the number of patients each nurse visits during a day, and the latter is achieved by balancing the work pressure. Based on the problem characteristics, one may consider the number of visited customers or the length of the tour assigned to each driver as the workload by adding a second objective function to the problem or using balance constraints (Mancini et al., 2021). Kritikos and Ioannou (2010) propose the balancing on the vehicle load in a vehicle routing problem with time windows (VRPTW). de Freitas Aquino and Arroyo (2014) propose a bi-objective formulation for the VRPTW and minimize the route length imbalance in the second objective function. An iterated local search (ILS) algorithm is used to find near Pareto-optimal results for the problem. Mancini et al. (2021) impose a lower bound on the number of customers that are assigned to a carrier in a collaboration setting that different carriers are able to share their fleets. They use an efficient metaheuristic and an ILS algorithm to solve the problem. For more detail on VRP with workload equity, the reader is referred to Matl et al. (2018).

This study introduces a vehicle routing problem with time windows and workload balancing (VRPTWWB) to improve laboratory resource management, balance the home testers' workload, and reduce transportation costs. To the best of our knowledge, this paper is the first study that considers COVID-19 laboratory's requirements, including workload balance and working time, while minimizing the total traveling costs. We consider the number of visited patients by a nurse each day as the workload. Although it may result in different shift duration for testers, it can reduce their exposure to possible infected patients and increase their safety. A medical laboratory is considered as the case study for this research. This laboratory has faced a massive demand for in-home PCR tests during the pandemic since it is one of the few laboratories that is accepted by airlines and international organizations requiring a valid negative PCR test result to serve their customers. The proposed VRPTWWB formulation aims to provide patients with high-quality services in their specified time, reduce the routing costs, reduce the number of testers, and balance the testers' workload. The main contributions of this paper can be summarized as follows:

Table 1. Sets, parameters, and decision variables

Sets	
\mathcal{V}	Set of all nodes including patients and laboratory, $\mathcal{V} = \{0, 1, \dots, \mathcal{V} \}$
\mathcal{N}	Set of all patient nodes, $\mathcal{N} = \{1, \dots, \mathcal{V} \}$
\mathcal{A}	Set of all arcs
\mathcal{K}	Set of testers, $\mathcal{K} = \{1, \dots, \mathcal{K} \}$
Parameters	
c_{ij}	Transportation cost from node $i \in \mathcal{V}$ to node $j \in \mathcal{V}$
t_{ij}	Travel time from node $i \in \mathcal{V}$ to node $j \in \mathcal{V}$
s_i	Service time at node $i \in \mathcal{V}$
e_i	The earliest time that patient $i \in \mathcal{V}$ can be visited
l_i	The latest time that patient $i \in \mathcal{V}$ can be visited
\mathcal{W}	The maximum working time for each tester predefined by the lab
P	Penalty cost for one unit of the maximum deviation
Decision Variables	
x_{ij}^k	1 if and only if tester $k \in \mathcal{K}$ visits patient $j \in \mathcal{V}$ right after visiting patient $i \in \mathcal{V}$
z_i^k	1 if and only if patient $i \in \mathcal{N}$ is visited by tester $k \in \mathcal{K}$
T_i^k	Time at which tester $k \in \mathcal{K}$ visits patient $i \in \mathcal{N}$
η	Maximum deviation among all testers' workload

- Developing a VRPTWWB mathematical model to meet laboratory's requirements, including workload balancing and working time.
- Developing an Adaptive Large Neighborhood Search (ALNS) algorithm to solve the given problem for large-sized instances.
- Applying the proposed model and metaheuristic algorithms to a real-case study.

The remainder of this study is organized as follows. Section 2 discusses the assumptions and formulations of the problem. In Section 3, we describe the main elements of our ALNS metaheuristic algorithm and computational results are provided in Section 4. We conclude the study in Section 5.

2. MATHEMATICAL MODELLING

In this section, a mathematical formulation for the VRPTWWB is presented. The proposed MIP model minimizes the transportation cost of testers as well as the non-uniformity of testers' workload.

Let $\mathcal{G} = (\mathcal{V}, \mathcal{A})$ be a complete directed graph where $\mathcal{V} = \{0, 1, \dots, N\}$ denotes the set of all nodes including laboratory and all patients. Node $0 \in \mathcal{V}$ is the laboratory from where all testers must start and end their routes. \mathcal{A} is the set of arcs, and \mathcal{K} is the set of testers. Each patient i must be visited in their time windows $[e_i, l_i]$, while t_{ij} represents the travel time from node i to node j , and c_{ij} is the cost of a tester traversing the arc. The work shift for each tester is \mathcal{W} hours meaning that they must return to the laboratory no later than \mathcal{W} hours. Parameter s_i represents service time of patient i .

The first decision variable of this problem is x_{ij}^k which equals 1 if tester k visits patient j after visiting patient i . Variable T_i^k is the time that tester k visits patient i . Table 1 summarizes the parameters, sets and decision variables of the problem. The mathematical formulation for this problem is as follows:

$$(VRPTWWB) \quad \text{minimize} \quad \sum_{(i,j) \in \mathcal{A}} \sum_{k \in \mathcal{K}} c_{ij} x_{ij}^k + P\eta \quad (1)$$

Subject to

$$\eta \geq \left(\sum_{i \in \mathcal{N}} z_i^k - \sum_{i \in \mathcal{N}} z_i^{k'} \right) \quad k \in \mathcal{K}, k' \in \mathcal{K}/\{k\} \quad (2)$$

$$\sum_{k \in \mathcal{K}} z_i^k = 1 \quad i \in \mathcal{N} \quad (3)$$

$$\sum_{j \in \mathcal{V}} x_{ji}^k = z_i^k \quad i \in \mathcal{N}, k \in \mathcal{K} \quad (4)$$

$$\sum_{i \in \mathcal{V}} x_{ih}^k = \sum_{j \in \mathcal{V}} x_{hj}^k \quad h \in \mathcal{V}, k \in \mathcal{K} \quad (5)$$

$$\sum_{j \in \mathcal{N}} x_{0j}^k = 1 \quad k \in \mathcal{K} \quad (6)$$

$$\sum_{i \in \mathcal{N}} x_{i0}^k = 1 \quad k \in \mathcal{K} \quad (7)$$

$$e_i \leq T_i^k \leq l_i \quad i \in \mathcal{N}, k \in \mathcal{K} \quad (8)$$

$$T_j^k \geq T_i^k + s_i + t_{ij} - M_{ij}^k(1 - x_{ij}^k) \quad i \in \mathcal{V}, j \in \mathcal{N}, k \in \mathcal{K} \quad (9)$$

$$\mathcal{W} \geq T_0^k - T_i^k + t_{0i} - M_{0i}^k(1 - x_{0i}^k) \quad i \in \mathcal{N}, k \in \mathcal{K} \quad (10)$$

$$x_{ij}^k, z_i^k \in \{0, 1\} \quad i \in \mathcal{V}, j \in \mathcal{V}, k \in \mathcal{K} \quad (11)$$

$$T_i^k \geq 0 \quad i \in \mathcal{V}, j \in \mathcal{V}, k \in \mathcal{K} \quad (12)$$

$$\eta \geq 0 \quad (13)$$

Objective function (1) minimizes the total transportation cost of testers and the total penalty of the maximum deviation of the testers' workload. The maximum deviation is modeled in constraints (2). Constraints (3) and (4) ensure that all patients are visited exactly once. Constraints (5) guarantee flow conservation. Testers start and end their routes at the laboratories due to Constraints (6) and (7). All patients must be served during their predefined time window which is ensured by constraints (8) and (9). Constraints (10) guarantee that a tester does not exceed his work shift duration. The nature of the variables and their domains are stated by constraints (11)–(13).

3. SOLUTION METHOD

In this section, we present an ALNS algorithm for solving the VRPTWWB. The solution representation is presented in Section 3.1. The proposed algorithm for generating the initial solution is described in Section 3.2, and the structure of the ALNS algorithm is explained in detail in Section 3.3.

3.1 Solution representation

The encoding method for representing the solution is proposed by Shi et al. (2017). In this method, a list table is used for sorting the solutions, such that each row of the table is associated with a route of a specific tester. A tester's route starts and ends at the lab; thus, the first and the last elements of each list is the lab (depot). The remaining elements of the list represent the visiting sequence of the patients. This encoding is displayed in Fig. 1.

T1	Lab	13	3	8	6	Lab
T2	Lab	2	7	Lab		
T3	Lab	9	4	10	Lab	
T4	Lab	5	1	11	12	Lab

Fig. 1. An example of the solution representation

3.2 Initial solution

The tour-building algorithms for the VRPTWWB use two methods, including sequential and parallel algorithms. The former performs customer scheduling through the construction of one route at a time, whereas the latter schedules several routes simultaneously. Prior to beginning the processes, one can consider the number of routes either to be fixed or vary in a problem-dependent manner (Solomon, 1987). In this study, an approach proposed by Shahnejat-Bushehri et al. (2021) is adapted to our problem, which can rapidly generate initial solutions of high quality. For more details, the reader is referred to Shahnejat-Bushehri et al. (2021).

3.3 Adaptive large neighborhood search

This study develops an adaptive large neighborhood search (ALNS) in a simulated annealing framework as a solution method. Ropke and Pisinger (2006) introduced ALNS, which consists of removal and insertion algorithms. ALNS differs from traditional LNS in that it uses several removal and insertion heuristics that are selected based on collected statistics at each iteration, as well as a simulated annealing metaheuristic for the acceptance process. The ALNS has been used to solve several VRP variants, including the HHC with time windows (Di Gaspero and Urli, 2014; Liu et al., 2019), which is closely related to our problem. Several studies have demonstrated ALNS' superior performance in handling a variety of real-world transportation problems, such as orienteering (Santini, 2019), and routing problems (Goeke and Schneider, 2015; Keskin and Çatay, 2016; Schiffer and Walther, 2018). Overall, ALNS can be considered a reliable and efficient metaheuristic algorithm to solve routing and scheduling problems. A brief overview of the proposed ALNS's detailed implementation steps is given in the following subsections.

Neighborhood structure: Patients' requests for HHC services should be fulfilled within specific and usually tight time windows. The preserved visiting order does not allow traditional improvement operators such as 2-opt, 2-opt*, exchange operator, and a relocation move to improve the operation significantly as the nature of such operators is random. With restricted time windows for HHC services, adopting an inefficient operator would lead to a time-consuming neighboring solution construction process. Therefore, this study uses a modified insertion operator proposed by Shahnejat-Bushehri et al. (2021) which is capable of generating feasible neighboring solutions rapidly.

Fig. 2 depicts an example of the proposed insertion operator.

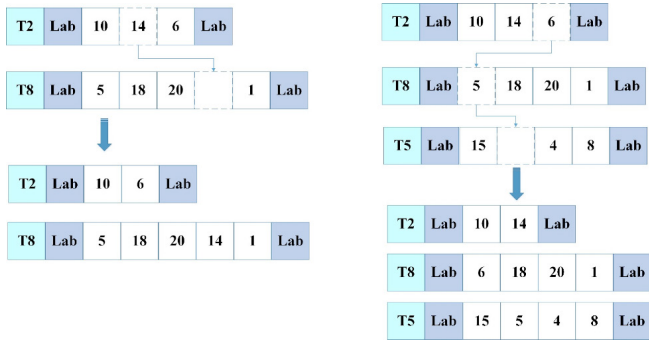


Fig. 2. An example of the modified insertion operator mechanism

Pseudo code of ALNS: In the ALNS, the large neighborhood search is extended by selecting each operator at each iteration based on their performance in previous searches. The entire search is broken down into segments. A segment is a number of ALNS heuristic iterations (i.e., 100 iterations). When starting each segment, the score of all operators is reset to zero. A simulated annealing acceptance criterion is used in this paper to diversify the solutions and to avoid being trapped in local optima. This algorithm starts with an initial solution and continues until the current temperature is lower than the final temperature. At each iteration, the operator described in the previous section is selected to remove q customers from the current solution and insert them back into other positions of the current solution. With different values for q , we can have multiple removal and insertion heuristics that can be used in the implementation of ALNS. The current solution is destroyed and repaired by one operator at each iteration. Each operator i at segment j has weight w_{ij} , and score π_i obtained during the last segment. At the start of ALNS, all operators have an identical weight of one and scores of zero. The probability of selecting an operator in each iteration is determined in the same way as in Ropke and Pisinger (2006), using the scores accumulated throughout the search.

There are three ways to increase an operator’s score. The operator’s score is improved by σ_1 if the operator can achieve a new global best solution. The score is enhanced by σ_2 , if the operator’s procedure produces a previously unaccepted solution and the new solution’s cost is lower than the current solution’s cost, and σ_3 , if the new solution is more costly than the existing one, but the solution was accepted. The weights of operators are modified at the end of each segment based on their performance as $w_{i,j+1} = w_{ij}(1 - r) + r \frac{\pi_i}{\theta_i}$ where θ_i is the number of times operator i is employed in the previous segment, and r is a reaction parameter that controls the weight adjustment’s inertia. The related operators are chosen independently for each segment using a roulette wheel selection process. The probability of selecting the i th operator for segment j is $w_{ij} / \sum_{k=1}^{\Omega} w_{kj}$, where Ω is the number of operators. The procedures for implementation of the ALNS is described in Algorithm 1. The algorithm starts with the production of the initial solution as explained in Section 3.2. The algorithm continues until the current temperature T_c is

Algorithm 1. ALNS

1. $CurrentSolution \leftarrow InitialSolution$
2. $BestSolution \leftarrow CurrentSolution$
3. **While** $CurrentTemp > TempLow$ **do:**
4. $j = 1, \pi_i, \theta_i = 0 \quad \forall i \in \Omega$
5. **For** 100 iteration **do:**
6. Probabilistically select an operator i and $\theta_i = \theta_i + 1$
7. $NewSolution \leftarrow operator(CurrentSolution)$
8. $\pi'_i = 0$
9. **if** $f(NewSolution) < f(CurrentSolution)$ **then:**
10. $CurrentSolution \leftarrow NewSolution$
11. $\pi'_i = \sigma_2$
12. **if** $f(CurrentSolution) < f(BestSolution)$ **then:**
13. $BestSolution \leftarrow CurrentSolution$
14. $\pi'_i = \sigma_1$
15. **end if**
16. **else:**
17. Randomly generate $r \in [0, 1]$
18. **if** $r < e^{-\frac{-(f(NewSolution) - f(CurrentSolution))}{T_c}}$ **then:**
19. $CurrentSolution \leftarrow NewSolution$
20. $\pi'_i = \sigma_3$
21. **end if**
22. **end if**
23. $\pi_i = \pi_i + \pi'_i$
24. **end for**
25. $CurrentTemp \leftarrow CoolRate \cdot CurrentTemp$
26. Update operator weights by $w_{i,j+1} = w_{ij}(1 - r) + r \frac{\pi_i}{\theta_i}$
27. **end while**

below the final temperature T_f . Non-improving solutions are accepted in order to prevent being trapped in a local optimum, as described in Algorithm 1.

4. RESULTS

In the following sections, small-size instances are solved using the CPLEX solver. When the number of customers (patients) increases, the solution times also increase rapidly, which makes using CPLEX inefficient for large instances. The proposed metaheuristic algorithm results are compared with the optimal results for the small-size instances, and the analysis of these results indicates that for the considered instances, the algorithm finds the optimal solutions in a much shorter amount of time. Finally, the algorithm

Table 2. Characteristics of the generated test problems for small-size instances

Parameters	Lower bound	Upper bound
$c_{ij} = t_{ij}$	20	60
S_i	10	20
e_i	0	360
$l_i = e_i + 30$	-	-

Table 3. Parameters and values for ALNS

Parameters	Values
$InitialTemp$	10
$TempLow$	0.1
$CoolRate$	0.9
q	{1, 2, 4, 5, 7, 10}
σ_1	30
σ_2	1
σ_3	10

Table 4. Experimental results for the small-size instances

CPLEX						ALNS			
NO	NC	NT	TC	η	CT(s)	TC	η	CT(s)	Gap*(%)
1	3	3	265.60	0	0.20	265.60	0	3.13	0
2	4	2	190.94	0	0.30	190.94	0	3.15	0
3	5	3	297.96	1	0.80	297.96	1	3.34	0
4	6	2	316.56	0	0.30	316.56	0	4.31	0
5	7	3	315.86	1	0.40	315.86	1	4.53	0
6	8	3	337.96	1	0.80	337.96	1	4.32	0
7	9	4	436.71	1	0.60	436.71	1	6.98	0
8	10	5	484.44	0	1.40	484.44	0	6.83	0
9	12	5	550.56	1	2.31	550.56	1	5.93	0
10	13	6	614.52	2	1002.27	614.52	2	7.61	0
11	14	5	702.36	1	240.43	702.36	1	8.02	0
12	15	6	756.26	1	408.20	756.26	1	8.13	0

* Relative gap compared to the results obtained by CPLEX

is applied to real data from the aforementioned laboratory, and the results are compared with the implemented routes over a six-day horizon.

4.1 Experimental results for small-size instances

The first set of experiments is conducted to show the efficiency of the proposed metaheuristic algorithm. These experiments are small-size instances, which can be solved optimally by general purpose optimization solvers within an acceptable time. In all of the test problems, parameters are generated by a uniform distribution, as shown in Table 2.

CPLEX 12.10.0 is used to solve the problems optimally. The proposed ALNS algorithm is employed to solve the same instances, and their results are compared with the optimal solutions. The ALNS algorithm is run on an Intel Core i7 2.00 GHz CPU with 16 GB of RAM by MATLAB 2017. The main parameters for the ALNS algorithm are shown in Table 3. The results of this comparative experiment are provided in Table 4, where NO, NC, NT, CT, and TC stand for the instance ID, the number of serviced customers, the number of testers, the computing time, and the total traveling cost. For the number of testers, the minimum possible value which can obtain a feasible solution is considered for each instance. The proposed metaheuristic algorithm's results are optimal for all 12 instances in Table 4, requiring far less computing time than the CPLEX solver for larger instances. Due to the complexity of the problem, the proposed ALNS algorithm can be an alternative to find near-optimal solutions within an acceptable time. Therefore, the proposed algorithm is used for our case study.

4.2 Case study

In this part, the data are obtained from a medical laboratory for six days. The scheduling manager must assign the patients to the testers and define the routes on each day. After obtaining the patients' locations, we used Google Maps to find the approximate location of each patient in a 2D plane. We define the lab as the depot located at point (15,15), and other locations are defined accordingly. After receiving a request, A patient is offered a 15-minute time range for tester arrival, which is considered as the model's time window. The maximum number of testers is nine due

to the medical laboratory limit, yet the algorithm may choose to use a lower number of testers that can reduce the costs.

Table 5 demonstrates the transportation costs, the number of testers, and η for both the manual procedures by the medical laboratory and the suggested routes found by the algorithm for each of the six days. The CPU time of the solution method and the relative solution improvement is also provided. An average of 12.66% improvement in the total traveling cost is obtained compared to the laboratory's manual planning. Also, the ALNS improves the workload balancing of the testers.

5. CONCLUSION

Since the beginning of the coronavirus outbreak, governments have been working to establish programs that will ensure access to rapid and reliable testing. Testing for COVID-19 is one of the essential strategies to prevent the spread of infection, and there are several laboratories that offer home testing services. In order to obtain a reliable plan to address a routing and scheduling problem arising from the logistic activities of these laboratories, this study provides an optimization model based on VRPTW that additionally considers workload balancing. To solve the proposed model, we developed an ALNS algorithm with a new insertion operator to solve large-size instances.

We conducted a series of experiments to test the proposed ALNS. The results obtained from solving the mathematical model using the CPLEX solver are compared to the results of the proposed metaheuristic method. The results obtained from different instances show that the proposed metaheuristic method performs well in terms of obtaining the optimal objective function value on small-size instances. After demonstrating the efficiency of the ALNS, this algorithm is used to solve instances arising from a real case study, which contains six planning days in a medical laboratory. The ALNS algorithm obtained a 12.66% improvement in comparison to their manual planning within a very short period of time, which is only 26.30 seconds on average. In our future works we aim to improve our assumption by considering more health related factors such as patients waiting time in the objective function. In addition, we will apply a sensitivity analysis to illustrate models' reaction to different parameter settings.

Table 5. Comparison of the ALNS results with those of the laboratory in real-world case study.

Day	NC	Manual procedure			ALNS solution				Improvement(%)
		TC	NT	η	TC	NT	η	CPU time (sec)	
1	68	350.72	7	11	311.99	7	3	23.33	12.41
2	62	365.84	7	7	302.95	6	5	27.93	20.76
3	69	360.28	6	8	328.25	6	8	32.27	9.76
4	65	356.82	8	10	308.19	7	6	26.42	15.78
5	56	340.26	7	10	306.16	6	8	20.99	11.14
6	70	368.88	6	4	347.66	6	3	26.88	6.11
Avg	-	357.13	6.83	8.33	317.53	6.33	5.50	26.30	12.66

Considering uncertainty in the travel time of the testers could be a possible future direction for this study. This can be done either by using stochastic programming or by using a dynamic horizon after visiting each node by a tester. One can also apply service-level on demand satisfaction to make sure a specific portion of the orders are always met by the laboratory. Another interesting topic would be using the idea of crowdsourcing in this problem based on distributing testing kits throughout the city and collecting them at specific times.

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