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Towards Smart Healthcare: UAV-Based Optimized Path Planning for Delivering COVID-19 Self-Testing Kits Using Cutting Edge Technologies

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Abstract: Coronavirus Disease 2019 (COVID-19) has emerged as a global pandemic since late 2019 and has affected all forms of human life and economic developments. Various techniques are used to collect the infected patients' sample, which carries risks of transferring the infection to others. The current study proposes an AI-powered UAV-based sample collection procedure through self-collection kits delivery to the potential patients and bringing the samples back for testing. Using a hypothetical case study of Islamabad, Pakistan, various test cases are run where the UAVs paths are optimized using four key algorithms, greedy, intra-route, inter-route, and tabu, to save time and reduce carbon emissions associated with alternate transportation methods. Four cases with 30, 50, 100, and 500 patients are investigated for delivering the self-testing kits to the patients. The results show that the Tabu algorithm provides the best-optimized paths covering 31.85, 51.35, 85, and 349.15 km distance for different numbers of patients. In addition, the algorithms optimize the number of UAVs to be used in each case and address the studied cases patients with 5, 8, 14, and 71 UAVs, respectively. The current study provides the first step towards the practical handling of COVID-19 and other pandemics in developing countries, where the risks of spreading the infections can be minimized by reducing person-to-person contact. Furthermore, the reduced carbon footprints of these UAVs are an added advantage for developing countries that struggle to control such emissions. The proposed system is equally applicable to both developed and developing countries and can help reduce the spread of COVID-19 through minimizing the person-to-person contact, thus helping the transformation of healthcare to smart healthcare.

Keywords: healthcare; COVID-19; self-testing kits; unmanned aerial vehicles (UAVs); route optimization; delivery systems; artificial intelligence (AI); smart healthcare

1. Introduction and Background

Coronavirus Disease 2019 (COVID-19) has taken the world by surprise due to its faster spread. It has emerged as a life-threatening disease, affecting people from all age groups. The number of cases is rapidly increasing globally. According to worldometers.info (https://www.worldometers.info/coronavirus/, accessed on 4 July 2021), more than 184 million people were registered as being infected. More than 168 million are recovered patients out of the reported cases, around 12 million are currently active, and sadly, more than 3.9 million lives have been lost [1]. The presence of many active cases and the potential of losing lives makes the management of COVID-19 very critical if the world is to get out of this pandemic.

Accordingly, various testing clinics, sites, pop-up hospitals, and mechanisms have been introduced worldwide to get information about COVID-19 and instigate proper responses to deal with it [2]. However, the situation is still critical, and the virus is quickly spreading globally, with more and more potential for life-threatening scenarios, especially for the vulnerable and elderly population [3]. Thus, the vulnerable populations, such as those of 70 years of age or over, those with organ transplants or immunosuppressive therapy, those who have had a bone marrow transplant in the last 24 months, those who are on immunosuppressive therapy for graft versus host disease, those having blood cancer such as leukemia, lymphoma or myelodysplastic syndrome and those having chemotherapy or radiotherapy are at the highest level of risks that can lead to deaths in case they are affected by COVID-19.

Among the measures introduced by the countries worldwide, international border closures to travelers from other countries are commonly implemented by countries such as Australia, the USA, the UK, and others [4]. Other steps include a state-wise curfew imposition, such as in Australia or the USA, which have restricted its residents from traveling interstate, and in some cases, residents are confined to their homes due to localized lockdowns [5]. Figure 1 shows the current statistics of COVID-19 cases in different states of Australia. Similarly, mandatory hotel quarantine measures for returning locals are also imposed in many countries worldwide, where travelers from other countries are subjected to a minimum of 14 days quarantine in local hotels [6].

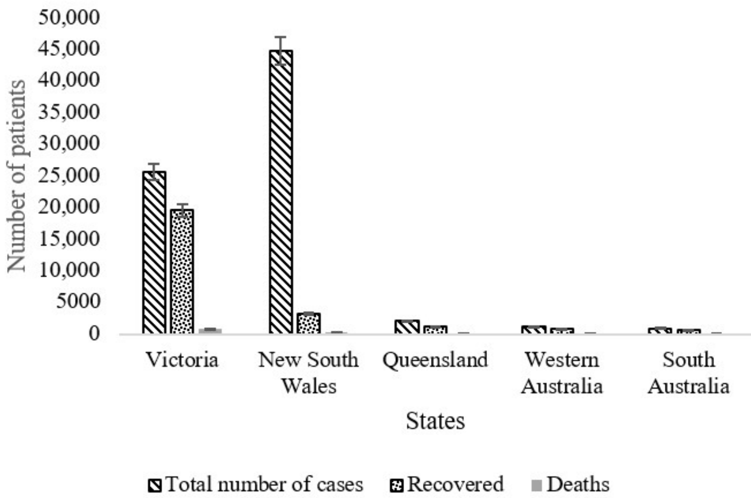


Figure 1. Number of COVID-19 cases in different states.

Pakistan is a neighboring country to India, where the highest COVID-19 cases were recently recorded. India has emerged as the country with the highest reported daily cases of COVID-19 in the last month. However, unlike its neighbors, Pakistan has successfully tackled or, in other words, managed the pandemic in a much better way, with significantly lower cases, higher recoveries, and much lower deaths. Figure 1 shows the distribution of active and recovered COVID-19 cases in Pakistan and their associated deaths. Figure 2 is developed by the authors based on the data provided by the government of Pakistan's official portal (covid.gov.pk, accessed on 4 July 2021) [7]. Accordingly, 95% of the COVID-19 patients in Pakistan have recovered, with only 3% active cases and 2% deaths. This is thanks to effective strategies, such as the smart lockdowns, which reduced the increasing cases from 13.14% to 6.5%, effectively halving the number of cases and the spread of the virus, resulting in more time to deal with existing patients and reduce the burden on the country's medical resources [8]. The current positivity rate is less than 2% per 100 COVID tests in Pakistan. Based on its successful strategies, the government aims to be extra vigilant about the situation before it gets out of hand like its neighboring countries. Accordingly, researchers are encouraged to investigate various strategies that can help the government effectively manage the COVID-19 situation and keep the cases to a minimum. To help materialize this goal, the current study proposes using AI-powered unmanned aerial vehicles (UAVs) to deliver self-testing kits to potential Pakistani patients for reducing, if not eliminating, the virus spread in Pakistan.

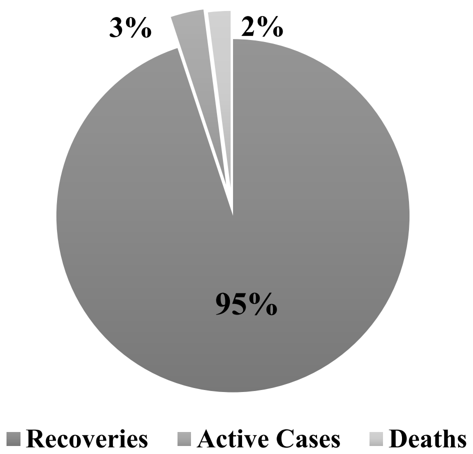


Figure 2. Pakistan COVID-19 statistics (data source: covid.gov.pk, accessed on 30 July 2021).

Among the techniques used to track and combat COVID-19 in the healthcare sector, industry 4.0 technologies [9], Internet of things (IoT) [10], artificial intelligence (AI) [11], machine learning [12], and other techniques are used worldwide [13]. However, the use of AI-powered UAVs in combating COVID-19 has not been explored to date for delivering the self-testing kits. This provides a research gap targeted in the current study.

UAVs are increasingly utilized in the world for addressing various needs and responding to disasters in the world. With the advent and utilizing of disruptive digital technologies, such as Big9 technologies, including virtual and augmented reality, drones, robotics, AI, and others, UAVs and other aerial vehicles are increasingly investigated in the world for pertinent applications [14–18]. Accordingly, UAVs have been explored in disaster management, such as flood detection and response planning [19–21], smart real estate and city management [14,22–25], agriculture, and others [26]. Similarly, in smart city applications, AI-powered UAVs have been used in smart transportation and new mobility options [27]. In health care, UAVs have been used for preventing cyber-attacks [28], information distribution [29], medical supplies dispatch, and others [30]. In healthcare, these AI-powered UAVs have been used for surveillance to combat pandemics [31], blockchain-envisioned security framework for AI-enabled IoT-based drone-aided healthcare services [32], and smart communication systems [33]. Other studies have proposed using mixed 5G and AI-powered UAVs for various applications in healthcare as means for transformation into a smart healthcare sector [34].

However, UAVs have not been explored for dispatching and collecting self-testing COVID-19 kits to potential patients to date, which is a novelty of the current study. The closest study is Euchi [30], who proposed delivering health care systems to patients using UAVs. Similarly for delivering materials to others, Ullah et al. [35] proposed UAV based delivery mechanism for delivering advertisement materials to customers, but a sophisticated AI-powered system for delivering self-testing kits and bringing them back to the testing clinic has not been explored to date. The current study targets this gap and provides a holistic mechanism for delivering such self-testing kits to potential patients in a target region of Islamabad, Pakistan. Another aspect related to the novelty of the current study is that it targets a developing country and proposes a cost-effective and affordable solution for the government and private organizations to dispatch and collect COVID-19 samples. Alternate options, such as developing special function facilities or using mobile sample collection vans, may burden the economies of the developing countries that are already struggling to manage their expenses. Thus, such a simplistic, cost-effective system for sample collection may help reduce the cases in developing countries with minimum investments. The UAV path is optimized using four key path optimization algorithms, and the results are presented and discussed to propose a sophisticated delivery and collection system. Furthermore, the reduced carbon footprints due to such UAVs are the added advantage that can tackle the air pollution concerns in developing countries such as Pakistan.

Due to brick kilns, older unmaintained cars, and transport systems in Pakistan, air pollution is rising. Accordingly, Pakistan was second among 98 countries with the worst air quality, with an average 156 air quality index in 2020. As of 2021, it is ranked at the fourth position in terms of the countries having the worst air quality, and the air quality has deteriorated further to an average of 167 [36]. This calls for reduced air pollutants and carbon footprints to be focused on a priority basis. The challenges are increased due to COVID-19, where patients use more personal transport, contributing to environmental pollution and poor air quality for getting tested or generally avoiding mixing with others. Similarly, the older type of delivery vehicles with poorly performing engines having increased carbon content emission adds to the deteriorating air quality. Therefore, it is imperative that in all the delivery mechanisms suggested for different deliveries in Pakistan, the impact on air and associated carbon footprints are considered. Accordingly, this study humbly contributes to lowering carbon footprints associated with delivering COVID-19 kits and other deliveries made through cars and trucks. It proposes an AI-powered UAV-based delivery mechanism to deliver COVID-19 kits to potential patients and bring them back to the hospital. The UAV paths are optimized using four key vehicle routing algorithms, greedy, intra-route, inter-route, and tabu, to minimize time and optimize the routes. Four cases with 30, 50, 100, and 500 patients and subcases involving 10, 20, 30, 50, and 100 UAVs are investigated for delivering self-testing kits to the patients in Islamabad, Pakistan. The depot and UAVs launching ground are established in the PIMS hospital Islamabad. This will reduce human-to-human contact along minimizing the spread of COVID-19 with a reduction in air pollution associated with deliveries, which is another humble contribution of the proposed delivery system.

The rest of the paper is structured as below. Section 2 investigates the techniques used for collecting potential COVID-19 patients' samples worldwide. Section 3 provides the methodology adopted in the current study and explains the proposed system. The algorithms and their pseudocodes are also presented in this section, along with the proposed model. Section 4 discusses the results obtained from the path optimization and the number of vehicles required in various cases to dispatch and collect the test kits. Finally, Section 5 concludes the study and presents a future direction for expanding upon this study.

2. Techniques for Collecting COVID-19 Patient Samples

Multiple methods have been explored to collect potential COVID-19 samples from infected patients. Three methods are widely used throughout the world: collecting samples in special hospitals or pop-up clinics, drive-through clinics, or self-collections at home by the patients. The advantages, risks, and limitations of these methods are presented in Table 1. A nasal swab is inserted about an inch into the patients' nostrils in all the tests. In some trial cases, saliva samples are collected for testing. Blood-based tests are under trials as well. These samples are processed in labs, where COVID-19 may be detected in the samples. The results are available to the patients in 1–3 days.

Table 1. Methods used to collect COVID-19-infected patients' samples.

S. No	Method	Advantages	Risks and Limitations
1	Special Hospitals or Pop-Up Clinics	Qualified staff collecting samples; Reliable results	Risk of spread to other patients and staff; Long wait and queues
2	Drive through Clinics	Qualified staff collecting samples. Lower risk of spread from other patients; Reliable results	Long wait and queues; Potential infection from the collection staff
3	Self-Collections	No risk of spread from other patients. Speedy collection	The process may be tough to understand; Lack of qualifications of patients; Improper handling of test kits may result in public health risks

Owing to the significant growth of COVID-19 cases, many countries have set up special hospitals and pop-up clinics to collect samples of potentially infected patients. These are administered by qualified staff equipped with proper personal protective equipment (PPE). However, such setups risk spreading the virus to other patients and staff, especially due to the long queues, more exposure time, and sharing of the same space by the patients [37,38]. Other methods include the drive-through clinics introduced in developed countries such as the USA, UK, and Australia. An advantage of these setups is that the risk of spread from other patients is significantly lowered due to patients using their private vehicles. Qualified staff equipped with PPEs can collect the sample for reliable results. However, there is a risk of potential infection from the collection staff [39]. Furthermore, this method is constrained by long wait times and queues. Some patients may have to wait hours, and in some cases, they are asked to come back another day to get their samples collected. In addition to this, cars and other transportation sources used by these patients add to air pollution, resulting in increased carbon footprints that can otherwise be controlled using alternate COVID-19 testing methods.

Self-collection of patient samples at homes is changing the COVID-19 sample collection procedures. It is an effective way of collecting samples with a very low risk of spreading the virus. According to Nagura-Ikeda et al. [40], the earlier the sample is collected, the more reliable the results will be. According to the authors, COVID-19 was detected at significantly higher percentages (65.6 to 93.4%) in specimens collected within nine days of symptom onset than in specimens collected after at least ten days of symptoms (22.2 to 66.7%) and in specimens collected from asymptomatic patients (40.0 to 66.7%). Thus, the samples must be collected as soon as possible. However, such self-collection methods are not common, especially in developing countries presenting a gap targeted in the current study. Accordingly, the current study explores the application of UAV-based COVID-19 self-collection test kit delivery and sample collection in a developing country (Pakistan).

For self-collection at home by the patients, different self-testing kits are available on the market. This includes the Nomad coronavirus antibody self-test kits, which cost £60 per person in the UK. The kit includes a blood test kit, online video consultation with a Nomad clinician, and the information on accessing the results [41]. In the USA, similar kits are made available by Johns Hopkins Medicine to be collected through an appointment [42]. These kits can be delivered by different means to the patients, which adds to air pollution and may not be ideal for developing countries. The EverlyWell COVID-19 test home collection kit was made available by the EverlyWell corporation in the USA. This kit costs around US $109 and involves a lower nasal swab sample collection. The results are available after 72 h once the sample is received. Another USA-based saliva test is available through the organization known as HERS, with a base price of US $150.

Similarly, Kroger Health, another USA-based pharmaceutical company, has prepared self-testing kits available throughout the country. Their process involves gathering the kits, a video call, washing hands, specimen collection, labeling the sample, packing the kit, and shipping it to the lab [43]. While these organizations have made it accessible and easy for the patients to obtain and use the self-testing kits, the shipment and dispatching process is a bit complicated and may involve virus spread risks. Furthermore, the added pollution due to transportation method is also concerning for developing countries with older and unmaintained cars and delivery trucks. Furthermore, as previously discussed, the earlier the sample is collected, the more reliable the results will be. Owing to this, the current study streamlines the process of testing kits dispatch and collection using AI-powered UAVs to dispatch and collect the samples from the patients within minutes. This is helpful for tackling the air quality issues due to transportation in developing countries. Table 2 lists some kits used globally for self-collection of COVID-19 samples and their prices.

Table 2. Self-collection kits manufacturers, collection process, location, and price.

Collection Method	Kit Manufacturers and Name	Collection Process and Results	Location	Price
Nasal Swab	Everlywell COVID-19 Test Home Collection Kit	Kits shipped to patients with instructions; Return instructions mentioned; Results available online within 72 h when the lab receives the sample.	USA	$109
	Pixel by LabCorp COVID-19 Test	Test mailed out after the survey; Collection instructions mailed; Samples must be shipped back that same day; Results available within 24–48 h of the lab's receipt of the sample.	USA	$119
	LetsGetChecked Coronavirus Test	Online assessment marks eligibility; The patient will collect the sample and send it back to the lab; Results available on online accounts in 24 to 72 h.	USA	$119
	Picture's COVID-19 test by Fulgent Genetics	Eligibility assessment determines kit dispatch; samples are sent in a pre-labeled box; A digital report will be available in an online portal in 1 to 2 days; Optional telehealth consultation to discuss the results.	USA	$119
	Kruger Health COVID-19 Test Home Collection Kit	Telehealth visits to determine eligibility; Test kit shipped; Collection and return explained; In-person drop-off available; Results available within 72 h of the lab receiving the sample.	USA	-
Saliva-Based	For Hims & Hers Saliva Test Kit	Initial questionnaire to determine eligibility; Test kit shipped overnight; Collection and return explained; Results available within 3 to 5 days of the lab receiving the sample.	USA	$150
	Phosphorus COVID-19 PCR Test	Order test and complete online medical screening; At-home sample collection kit shipped; Test results available within 72 h from the lab's receipt of the sample.	USA	$140
	Vault COVID-19 Test Kit	Risk factors and symptoms described online; A test kit sent to the patient; An online telehealth provider guides sample collection; Sample sent back via overnight shipping; Test results available 48 to 72 h after the sample arrives at the lab.	USA	$150
	Vitagene COVID-19 Saliva Test Kit	After a questionnaire, a test kit is sent via express mail; Sample collected as per instructions; Sample returned via express mail; Results available within 72 h of the lab receiving the sample.	USA	$129
	P23 Labs Unsupervised COVID-19 Test	Initial questionnaire to determine eligibility; Test shipped out; Patients should send back the sample within 24 h of collection; An email sent when test results are ready; An opportunity to talk to a physician about the result.	USA	$142
	TMB Coronavirus Self-Test Kit	Receive an activation link for MyTMB; Visit the site and complete the request form; Sample collected as per instructions; Post your pre-addressed package in any post box; Patients contacted when results available.	Ireland	£160
Blood-Based	Nomad Coronavirus Antibody Home Test Kit	Kit ordered online; Video consultation with a physician to determine eligibility; Kit shipped; Sample collected through video assistance; The results are explained on a video call.	UK	£60
	HIVE Coronavirus COVID-19 Test-Home Self-Test Kit	Blood test kit ordered online; Test strips provide indications of COVID-19 biomarkers; Used for secondary diagnosis of COVID-19	UK	£110

The key advantages of using AI-powered UAVs for self-collection kits include significant COVID-19 spread risk reductions due to no contact with other patients or having to share the same space for an extended amount of time. The speed of collection is another advantage of such setups. Additionally, the reduced carbon footprints and air pollution due to less reliance on motor vehicles is a key advantage. However, self-testing kits are banned in some countries such as Australia, and unauthorized usage may result in heavy fines; hence, COVID-19 self-collection kits cannot be advertised to consumers in Australia [44]. Thus, for a global application, new laws and regulations or significant changes to current laws may be needed.

3. Method and Material

In Pakistan, potential COVID patients must visit the nearest hospitals to deliver their samples to be checked for coronavirus. This process is dangerous, as a person who is not infected is more likely to catch a virus if they visit the hospital and share the same space with an infected person. Similarly, the older and lesser maintained cars and transportation means add to air pollution and associated carbon footprints, which is already a challenge for Pakistan. This indicates the need for an automated procedure consisting of UAVs that visit each person's house and deliver a COVID-19 self-testing kit. The patient can take their sample and attach it to the AI-powered UAV so that it can be brought back to the hospital for further testing and reporting. This will minimize the risk of people catching the virus or transferring it to others due to minimum interactions.

As mentioned in Section 2 of the current study, any available testing kits can be used for this purpose. UAVs can automate the procedure through AI, and each UAV will visit the house of each suspected patient and deliver a kit to them that can be attached to the UAV and taken to the hospital to be tested by a medical expert. The advantage of this approach is that no human resources, such as drivers or self-visits of potentially infected patients, will be required. Hence, human contact can be minimized, thus reducing the risks of spreading the virus. Additionally, the additional time consumed due to heavy traffic can be reduced, thus reducing the environmental footprints and burden on healthcare facilities and saving precious time.

The limitation is that the UAV is a battery-operated vehicle; the battery can expire after a particular time duration. Hence, each UAV has a specific flight duration during which it must complete its mission. For most commercially available UAVs, the flight time is between 45 min to 2 h. Since there is no specific UAV used in the current study, the details about study-specific UAV cannot be shared; however, most commercial UAVs that can be used for similar objectives have the characteristics shown in Table 3. Table 3 shows six commercially available UAVs that can be used for delivering COVID-19 test kits.

As shown in Table 3, the drones have limited battery time; thus, the UAVs need to complete the trip within their battery time and return to the base point. This calls for the need to solve the vehicle routing problem (VRP) for the UAVs to complete their tasks in the minimum possible time and find the shortest travel distance for dispatching and bringing the samples. As time constraint is inherent in this scenario, the solution will be based on VRP with time windows (VRPTW). Different routing techniques can be used for scenarios such as Chinese postman problems, ant colony optimization, traveling salesman problems, and others [45,46]. However, the current study is based on VRPTW. Similarly, multiple algorithms exist for solving VRPs, such as the Multi-population memetic algorithm [47], firefly algorithm [48], genetic algorithm [49], multi-objective multi-factorial memetic algorithm [50], hybrid swarm intelligence algorithm [51], and modified discrete glowworm swarm optimization [52]. Among the hybrid swarm intelligence algorithm, the four key algorithms that are commonly used are inter-route, intra-route, greedy, and tabu [35]. These have been used in recent studies related to materials, kits, or package delivery [35]. For example, the greedy algorithm has been used by Mat et al. [53] for waste collection VRP issues. Inter- and intra-route algorithms have been used by Mourad et al. [54] for solving VRP related to ontology-based reasoning systems for logistics applications deployment.

Tabu was used by Montané and Galvao [55] for the VRP with simultaneous pick-up and delivery service. Similarly, Ullah et al. [35] used all four algorithms for real estate advertisement material in the COVID era. Based on these studies, the current case study paper uses these four algorithms for VRP related to delivering and collecting COVID-19 kits in Pakistan. Figure 3 shows the general flowchart of the methodology adopted in the current study, where the key processes of calling the UAV dispatch team, gathering patients coordinates, initiating VRP algorithms, delivering kits, collecting samples, and returning to the base are presented.

Table 3. Commercially available UAVs for delivering packages.

S. No	Name	Characteristics	Link Official Website
1	Wing	It can deliver packages up to 3.3 pounds. Customers do not interact directly with the delivery drone. It hovers around 20 feet above the ground. It has conducted more than 100,000 flights across three continents	https://wing.com/ (accessed on 4 July 2021)
2	Amazon Prime Air	It can deliver packages up to 5 pounds in 30 min. In addition, customers can interact with it.	https://www.amazon.com/Amazon-Prime-Air/ (accessed on 4 July 2021)
3	UPS Flight Forward	It can deliver packages weighing more than 55 pounds. Suitable for delivering medical kits. UPS Flight Forward has teamed with Matternet, an autonomous drone logistics platform, to deliver medical supplies to WakeMed hospital in Raleigh, North Carolina. It can operate at night.	https://www.ups.com/us/en/services/shipping-services/flight-forward-drones.page (accessed on 4 July 2021)
4	Wingcopter	It provides services for commercial and humanitarian applications, including medical air services, logistics, and others. It can carry weights up to 6 kg. Its flight range is up to 110–120 km, the wind resistance is 15 m/s on average with 20 m/s gusts, and the cruise speed is between 100–240 km/h.	https://wingcopter.com/ (accessed on 4 July 2021)
5	Zipline	It has been used in global healthcare, retail and e-commerce, and defense and disaster responses. It can fly at any time of the day or night. Its cruise speed is 101 km/h and can carry up to 1.75 kg (3.9 lb) of cargo. The flight time is 45 min, and an altitude of 80–120 m can be attained above ground level.	https://flyzipline.com/ (accessed on 4 July 2021)
6	DHL Parcelcopter	It can carry a payload of up to 4.4 pounds and travel at speeds of around 43 miles per hour.	https://www.dhl.com/discover/business/business-ethics/parcelcopter-drone-technology (accessed on 4 July 2021)

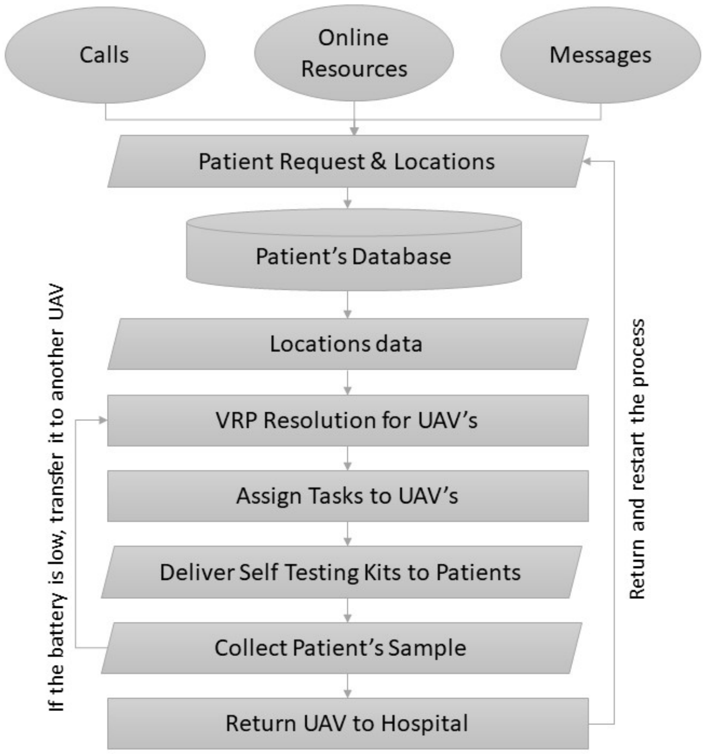


Figure 3. Methodology flowchart.

3.1. Case Study Area, Sample Delivery, and Collection

The case study area in the current study is Islamabad, the capital of Pakistan, as shown in Figure 4. The number of COVID-19 cases is relatively controlled in this area, and the government can keep it that way by introducing sophisticated sample collection techniques. Islamabad is the capital of Pakistan, which is situated in the northern part of the country. The total population of Islamabad is 1,014,825 as per the 2017 data. The total confirmed COVID-19 cases to date are more than 82,000, with 780 deaths recorded as of 4 July 2021 [7].

(**a**) (**b**)

Figure 4. Maps of the target area. (**a**), Islamabad Area; (**b**), The PIMS Hospital area.

The UAVs are proposed to be launched and controlled from one of the main hospitals in Islamabad, named the Pakistan Institute of Medical Sciences (PIMS). It is one of the region's leading tertiary level hospitals and includes 22 medical and surgical specialist centers. The hospital is in the G8 sector of Islamabad, situated at the center of Islamabad; thus, UAVs launched from G8 can have a minimum distance to all points within the Islamabad region.

There must be at least one depot for dispatching and collecting the samples where all the UAVs reside. In the current study, the helipad present at the PIMS hospital will be used as the launching and landing ground for the UAVs. After completing their missions, the UAVs will land on the same depot, and the samples can be taken for analysis to the testing lab at the PIMS. Each house of each patient submitting a sample is considered a node. The paths connecting the nodes and the depot are called edges in the path planning literature. Each UAV follows a particular route, starting and ending at the same depot, that consists of a set of nodes and edges. The mission of a UAV is completed when it completely follows the assigned route and reaches back to the depot safely. This is achieved through AI. Figure 5 shows such a sample network in the vehicle path, consisting of three distinct routes. Each route starts and ends at the same depot and consists of nodes to be visited by UAVs. The arrows are the edges that connect different nodes and the depot. Each edge represents a particular distance to be traveled by the UAV. In the current research, the PIMS helipad is considered the central depot location, where all the UAVs are kept, while each node represents a single patient location that is to be visited by the UAVs.

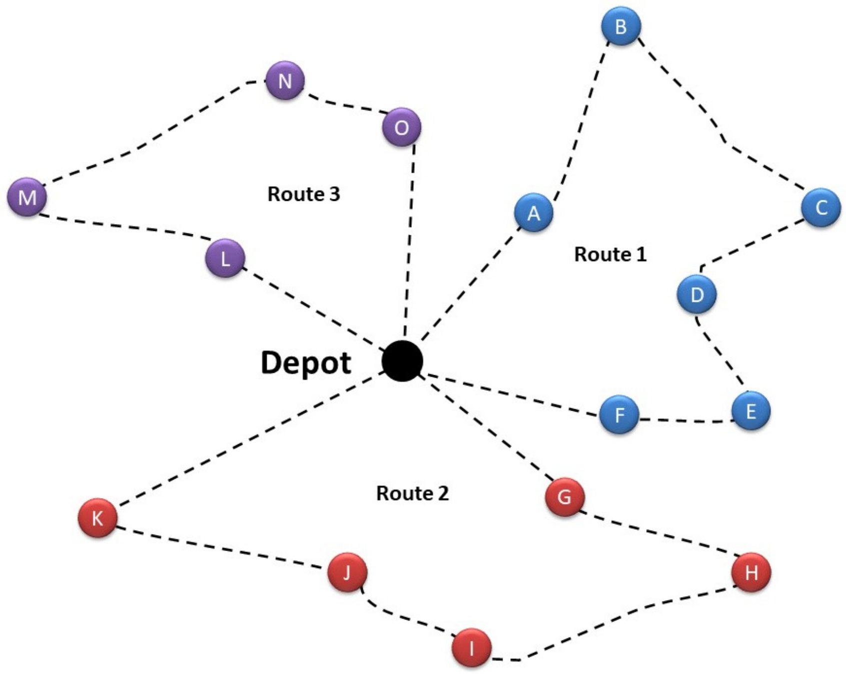


Figure 5. Sample network in VRPTW—numbers represent the costs (distance) associated with the edge.

Proposed Model

The VRP is proposed for a route, R_j for each drone, D_j in the set of available drones D. The constraints are given as below:

Each route starts and ends at the same location

the depot and node 0, $i = 0$, i.e., $i_1 = i_{|R_j|} = 0$, and $\left\{i_2, \ldots, i_{|R_j|-1}\right\} \subseteq \mathrm{N}\backslash\{0\}$, and

Each node is visited by one drone, i.e., $\cap_{j=1}^{|V|} R_j = 0 \ \wedge \cup_{j=1}^{|V|} R_j = N$.

The drones' travel cost is given as:

$$cost_{all} = \sum_{r \in N} \sum_{s \in N} c_{rs} x_{rs}$$

where x_{rs} is 1 where the route R_j is a connection between nodes r and s and 0 otherwise. The overall goal is to minimize the cost with the application of the above fitness function. The focus would be on the drone with the highest travel time or cost that is last to finish the route:

$$cost_{last} = max_{j \backslash j \in V} \sum_{r \in N} \sum_{s \in N} c_{rs} x_{rsj}$$

where x_{rs} is 1 when the route R_j for drone j is a connection between nodes r and s, and 0 otherwise. The added variable, j, calculates each route individually. To optimize the total time for all drones to finish their routes and for the last drone to finish its route is given as:

$$min_{f0}\left(z \times cost_{last} + (1 - \mathrm{z}) \times cost_{all}^{|V|}\right), z|0 \le z \le 1$$

where z focuses on optimizing the total travel time versus the time taken to complete the field tasks.

3.2. The Proposed UAV-Based COVID-19 Kit Dispatch and Collection System

Figure 6 shows the overall framework designed to optimize routes for UAVs to ensure timely delivery and collection of COVID-19 self-testing kits to the patients to move towards smart healthcare. It is a five-step process whereby the potential patients initiate a sample collection request, UAV is dispatched, and the sample is collected. The pertinent steps are explained in Figure 6.

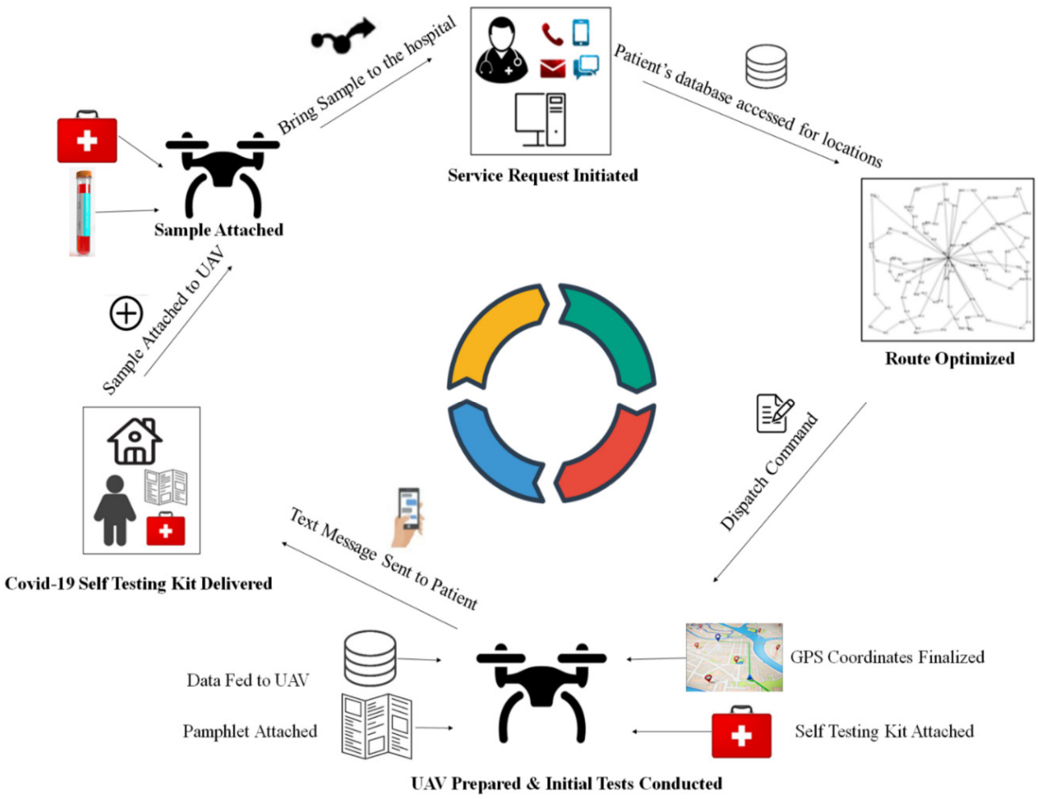


Figure 6. Framework designed for route optimization of UAVs for the delivery of COVID-19 self-testing kits.

3.2.1. Step 1

In this step, a request is initiated by the potential patient demanding a self-test COVID-19 kit. An immediate consultation or a questionnaire is required for qualifying the patient as eligible for delivering the kit. This can be done via a video call with the medical experts' panel in the UAV dispatch section or through AI-based automated questionnaires. Once a patient is determined to be eligible for the service, a service initiation request is sent to the UAV dispatch department. The personnel in the dispatch department ensures that the UAV, sample collection box, and self-testing kits are sanitized before dispatching to the patient. This way, it is ensured that UAVs do not carry the virus and, thus, do not spread it to the community.

3.2.2. Step 2

In this step, the patient location details are acquired from the dispatch team either directly or through the patient database stored in hospital records using AI. Once the record is obtained, the route-optimizing algorithms are run to find the best possible and shortest route to delivering the kits to the patient location and bringing the sample back to the hospital. In this step, the four proposed algorithms are run: greedy, intra-route, inter-route, and tabu, which are subsequently explained in the next section of the method.

3.2.3. Step 3

In this step, after the route is optimized using AI and the four algorithms, the optimized path GPS coordinates are fed into the UAV. A self-testing kit is added to a sealed box attached to the UAV. Care is taken to ensure that the box is sealed and cannot be affected by the environment while being transported through the UAV. The pamphlets and written guidance information about collecting the samples at home are added to the box, and UAV initiations and launch checks are performed for dispatching it to the target area. Finally, a text message is sent to the patient, informing them about the kits' arrival so that they can collect it from the UAV.

3.2.4. Step 4

In this step, the kit is delivered to the patient, and the UAV hands over the box with all details. The UAV lands in a safe location, puts the box down, waits for the patient to collect the sample, and puts the box in the same place as the COVID swabs. The UAV is equipped with cameras and sensors to interact with the patients, avoid risks to the UAV, and get everything on record. The UAV is further equipped with a microphone to interact with patients and ask any questions directly. Instructions are provided through the UAV speaker to the patient about how to collect the sample and leave the box safely. Once the sample is ready, the UAV sprays the box with sanitizing fluid and lifts it for delivery to the hospital. During this process, if the UAV battery runs low, it sends a signal to other UAVs that can replace it for the current operation, and the current UAV can return safely without extensive waits. The next UAV can collect the sample and take it back to the hospital. The primary UAV waits until the next UAV arrives to take over its job. A safety factor is kept in this case, where the UAV informs other UAVs in the swarm well in advance before its battery runs out. At the end of this step, the sample is taken back to the hospital.

3.2.5. Step 5

In this step, the UAV, depending upon its battery status and holding capacity, asks for permission to return to the depot or collect other samples, especially if informed by a nearby UAV whose battery is going down using AI. In this case, all the UAVs must have multiple sample collection capabilities with separate boxes and sanitizing abilities to avoid cross-contamination of samples. At the end of this step, the UAV can safely return to the depot or be rerouted to another location.

3.3. The Algorithms and Their Pseudocodes

As discussed in step 2 of the proposed dispatch system, four key vehicle routing algorithms are utilized in the current study: tabu search, greedy search, and intra-route, and inter-route heuristics [35]. A tabu search uses a nearest neighbor-based approach to find the most optimal solution in each iteration until the best one is achieved. The greedy search algorithm finds the current best solution without considering its viability in the next iterations. In the intra-route scheme, two edges from a route are removed, and two more edges are added to make a connected path. An inter-route scheme is used to reduce the number of vehicles. In this heuristic, two edges are selected from two unique routes, and their end parts are exchanged, resulting in two new routes. Figure 6 presents the pseudocodes of the four algorithms. Different algorithms exist for solving similar VRPs; however, as previously discussed, the current study is limited to the four mentioned algorithms.

4. Results and Discussion

The four algorithms are applied to solve the routing problems for UAVs in the current study. Different cases have been proposed to test the algorithms and plot their optimized paths. Four cases of patients have been considered, with the number of patients being 30, 50, 100, and 500. Five different sets of UAVs are used for each case: 10, 20, 30, 50, and 100, as shown in Table 4. The resultant number of UAVs used, the run time taken by the computer, and the optimized distance are shown for each case in Table 4. The results show that increasing the number of patients increases the overall distances to be covered and will need more UAVs. This also brings an increase in the total run time for all four algorithms. However, increasing the total number of UAVs in the depot does not guarantee a significant difference in the distances covered. Inter-route and intra-route heuristics bring noticeable improvements when compared to the greedy search results as shown in Table 4. The results generated by these methods take a lesser computational time and give a more optimized distance than the greedy search. However, the tabu search-based approach generates the most optimized solutions for all input parameters among the four considered algorithms. Hence, the tabu search heuristics can provide the best solution for the UAV routing and path optimization in the current study.

Table 4. Pseudocodes for (a) Greedy algorithm, (b) Tabu algorithm, (c) Intra-route algorithm, (d) Inter-route algorithm.

Algorithm	Pseudocode
(a) Greedy Algorithm	Start 1. Set an initial solution '*s*' and a neighborhood function '*x*' 2. Set *best* = *s* 3. Set iterations = 0 4. REPEAT UNTILL (Depth condition) DO 5. Set C = 0 6. Generate the next neighbor *i* € x(s) 7. Set c = c + 1 8. If fitness (*i*) > fitness (*best*) Then Set *best* = *i* End if 9. Set *I* = *best* 10. Set iterations = iterations + 1 11. End Do End
(b) Tabu Algorithm	Start 1. Produce an *IniSol* (Set of routes) using a nearest node rule, *s* represents distance, *k* denote demand and *i* is the solution. *IniSol* represents the initial solution 2. Determine fitness of *IniSol* as: $S_i = S_{route1} + S_{route2} + \ldots + S_{routen}$ $K_i = K_{route1} + K_{route2} + \ldots + K_{routen}$ $S_{routei} = S_{0,1} + S_{1,2} + \ldots + S_{n-1,n}$ $K_{routei} = K_1 + K_2 + \ldots + K_n$ 3. P_i is the fitness of the solution route $Pi = Si + Ki$ 4. Set best solution *BstSol* = *IniSol;* 5. Loop for n iterations, where in each iteration: 6. Create a new random solution *RndSol* applying a nearest rule between nodes. 7. Determine fitness of the *RndSol* 8. Check fitness of *RndSol* 9. If *RndSol* is better than *BstSol*, then *BstSol* = *RndSol*; Stop Loop 10. Output each route stored in the *BstSol* End

Table 4. *Cont.*

Algorithm	Pseudocode
(c) Intra-Route Algorithm	Start 1. Perform Greedy Search to generate solution graph 2. Reverse one path 3. Exchange paths of two consecutive nodes End
(d) Inter-Route Algorithm	Start 1. Perform Greedy Search to generate solution graph 2. Select 2 distinct nodes 3. Exchange their edges End

In some cases where the number of patients is much higher than the number of available UAVs, such as 500 patients covered with 10, 20, 30 or 50 UAVs, the system could not reach any possible solution. Such cases have been observed when the total number of patients is 100, and there are only 10 UAVs in the depot. More such scenarios are observed when the number of patients was raised to 500, and only 10, 20, 30, or 50 UAVs available in the depot. The cases with no viable solution are represented by N/A (Not Applicable) notation in Table 5. This also shows the limitation of UAVs, where each UAV cannot cover more than seven patients at a time. This limitation is due to the battery time of the UAVs and the distances covered within the stipulated time. In these cases, a battery time of 1 h and a UAV speed of 100 km/h are assumed. Furthermore, the UAVs are assumed to travel between 20–30 feet above the ground. The obstacles in the form of high-rise buildings, bridges, and mountains are automatically avoided through an AI-based intelligent system that extracts these features from the map and integrates them into the routing mechanism for constructing the travel path. Another assumption is that a UAV takes seven to eight minutes on average to dispatch, collect, and return the COVID kit. Other variables, such as wind speed and energy loss due to high heat, are not considered.

Table 5. Experimental results for solving VRP using Greedy Search, Tabu Search, Inter-Route, and Intra-Route Search Heuristics.

No. of Patients	Total UAVs	UAVs Utilized	Greedy Search		Tabu Search		Inter-Route		Intra-Route	
			Runtime (ms)	Distance	Runtime (ms)	Distance	Runtime (ms)	Distance	Runtime (ms)	Distance
30	10	5	343	39.65	100	31.85	114	32.2	117	38.05
	20	5	355	39.65	53	31.85	35	32.2	48	38.05
	30	5	352	39.65	55	31.85	35	32.2	52	38.05
	50	5	412	39.65	39	31.85	42	32.2	59	38.05
	100	5	353	39.65	49	31.85	29	32.2	85	38.05
50	10	8	525	58.95	204	51.1	111	51.8	110	56.8
	20	8	383	58.95	161	51.4	61	51.8	66	56.8
	30	8	359	58.95	156	51.15	63	51.8	62	56.8
	50	8	406	58.95	188	51.2	78	51.8	78	56.8
	100	8	402	58.95	169	51.35	94	51.8	109	56.8
100	10	N/A								
	20	14	355	102.45	266	83.75	109	89.8	94	99.55
	30	14	360	102.45	274	85.05	79	89.8	78	99.55
	50	14	421	102.45	240	88.2	89	89.8	108	99.55
	100	14	391	102.45	249	85	110	89.8	94	99.55
500	10	N/A								
	20	N/A								
	30	N/A								
	50	N/A								
	100	71	458	369.1	1148	349.15	366	349.4	203	361

Furthermore, the distance is calculated using the values generated by the UAVs multiplied by the unit value and divided by 1000 to convert into kilometers. For example, in the case of 30 patients and 10 UAVs, the distance calculated by UAVs is 793 units. In the current study, the unit distance is 50 m for plotting purposes. Hence, 793 $\times$ 50 m and divided by 1000 gives 39.65 km. Using these data, the total area of Islamabad, which is 220 km^2, can be easily covered with 15 or more UAVs if daily patients remain around 100. If the number of patients increased to 500, the number of UAVs needed would be 71 or more, as evident from Table 5.

Tabu may not be the ideal solution for computation times, as evident from Table 5. Instead, the balance shifts towards inter-route and intra-route algorithms when computation time is a priority. However, as the computation times are in milliseconds, this does not affect the response time and delivering a test kit to the patient. Thus, tabu is still the preferred technique for VRP in this case. For other studies where complex computations are involved and computation time is a concern, inter-route or intra-route algorithms may be more suited. Examples of such a scenario may include responding to disasters such as fires, evacuations, and locate and rescue services. Nevertheless, the current computations are performed on a core i7 laptop and has yielded speedy results. Given that such computers are installed in almost all modern smart healthcare facilities, computation speed remains a minor issue and not a significant concern.

Figure 7 shows the VRP graphs for four sample cases. Figure 7 "a" to "d" shows the graphs for the UAV routes generated by the four algorithms for a case of 30 patients and 20 UAVs. Figure 7 "e" to "h" shows the graphs for the UAV routes for a case of 50 patients and 20 UAVs. Figure 7 "i" to "l" shows the graphs for UAV routes for a case of 100 patients and 20 UAVs. In comparison, Figure 7 "m" to "p" shows the graphs for the UAV routes for a case of 500 patients and 100 UAVs. The graphs show that the lowest number of overlapping paths are obtained using the tabu search method. Additionally, the tabu search solutions are the simplest among all four methods. The solution graphs become more complex as the number of patients is increased from 30 to 500. This is because the number of nodes is increased, resulting in more corresponding edges and more routes.

Figure 8 shows the patient numbers (nodes) and the UAV dispatching and collecting the self-test kits for two sample cases. Figure 8a–d present the greedy, intra-route, inter-route, and tabu paths, respectively, for a case of 30 patients and 20 UAVs. Five UAVs are utilized in this case, pointing to the fact that only four UAVs can address the needs of 30 patients. Thus, the routes are optimized, and the UAV utilization is also smartly addressed. This is in line with the fact that a single UAV can address the needs of up to seven patients. Furthermore, not all UAVs are required to address seven patients. For example, as seen in Figure 8a, UAV4 (the last UAV) only attends two patients, i.e., Patient 7 and 2, and then returns to the depot. UAV3 (V3) attends six patients and returns to the depot, whereas UAV1 (V1) attends the maximum number of patients, i.e., seven patients. In this way, the batteries of some UAVs are saved to help the other UAVs in the swarm and share their loads.

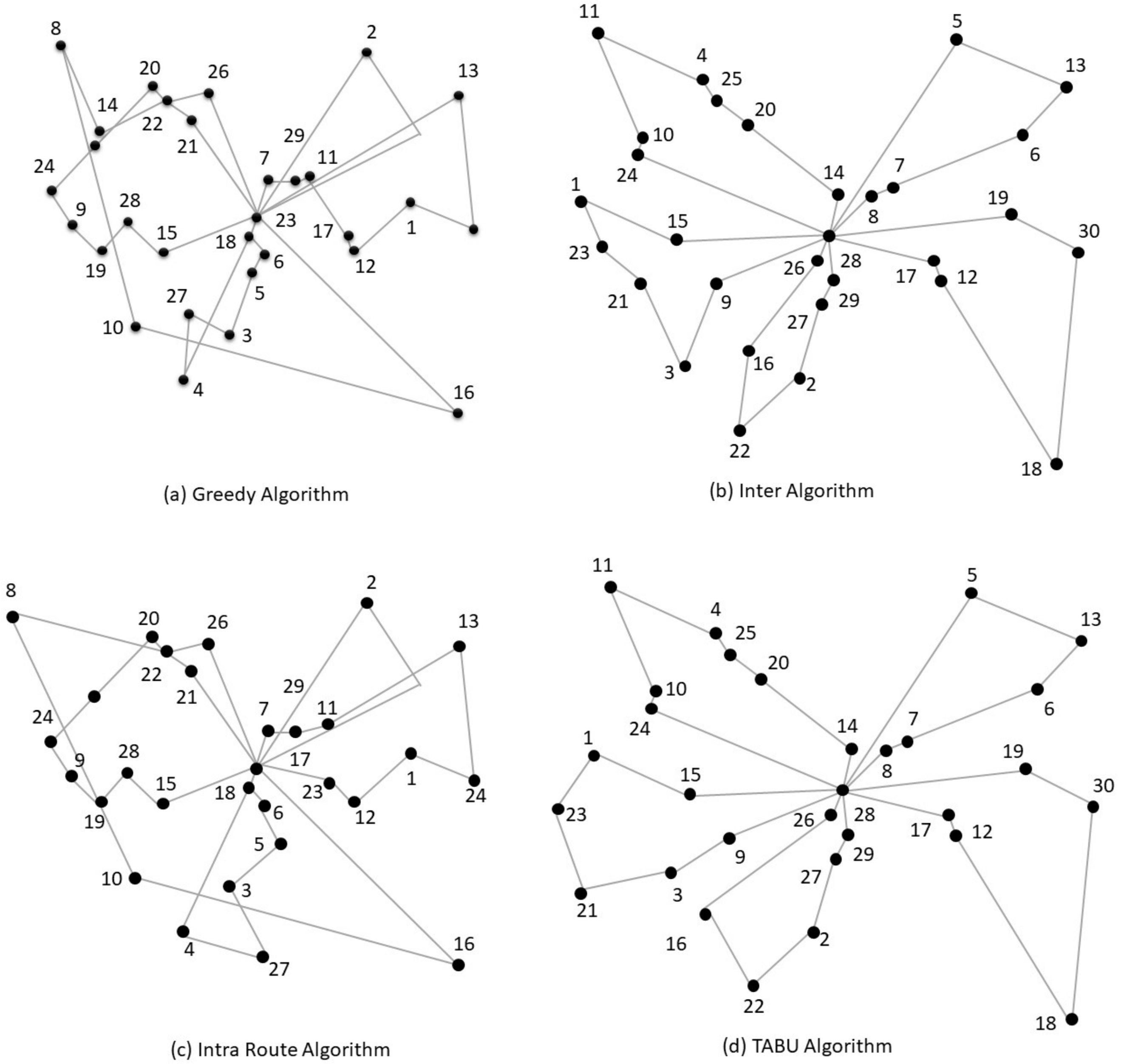
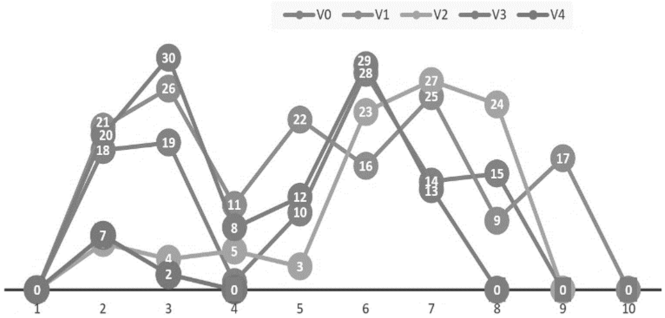
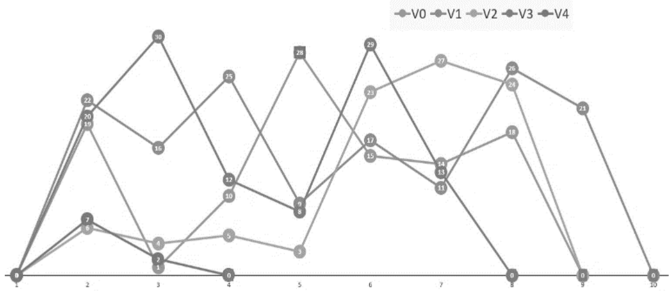


Figure 7. VRP Graphs Generated for sample cases.

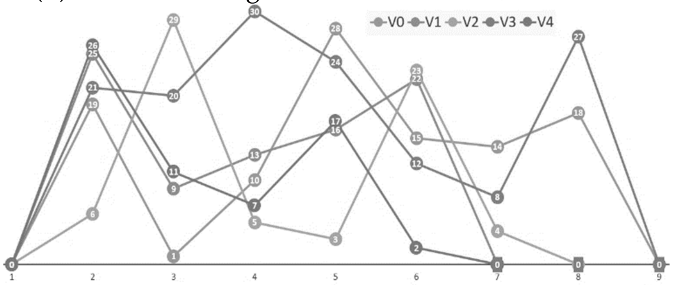
Similarly, as shown in Figure 8e–h, the results of paths planned by the four algorithms are presented when the number of patients is 50 and the UAVs available are 20. Again, not all UAVs are utilized; in fact, eight UAVs are used to address the patients' needs, deliver the kits, and collect the samples. As seen in Figure 8e, UAV7 is used for just one patient, followed by UAV6 and UAV5 for six patients and UAV3 and UAV4 for seven patients, whereas UAV2 and UAV1 are used for eight patients, as they have shared their workload with two other UAVs after completing their shifts. Hence, using the proposed sophisticated system, COVID-19 self-testing kits can be delivered and collected with ease from the potential patients without the risk of spreading the infections. This can help flatten if not eliminate the COVID-19 curve if adopted in smart healthcare globally.



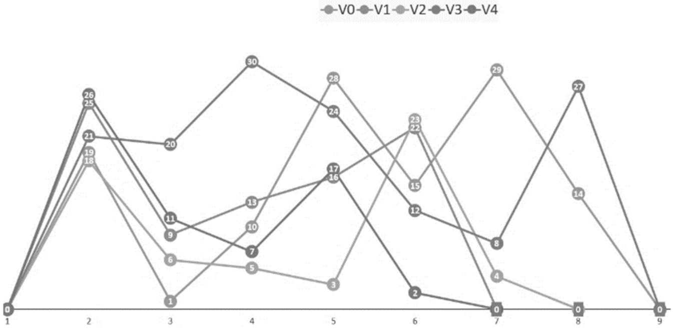
(**a**) Greedy Algorithm: Patients = 30, UAVs = 20



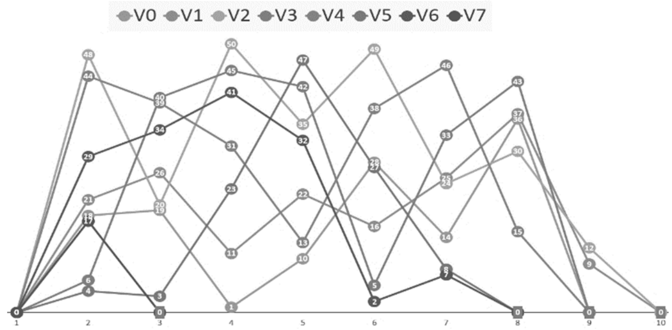
(**b**) Intra-Route Algorithm: Patients = 30, UAVs = 20



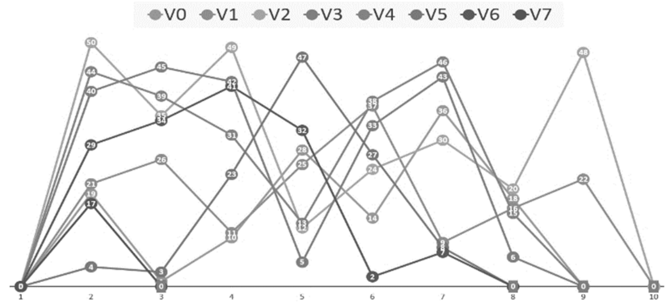
(**c**) Inter-Route Algorithm: Patients = 30, UAVs = 20



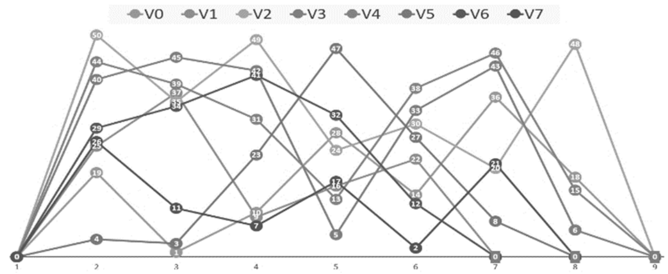
(**d**) Tabu Algorithm: Patients = 30, UAVs = 20



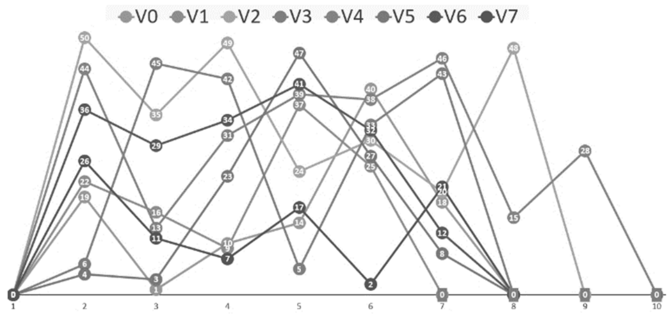
(**e**) Greedy Algorithm: Patients = 50, UAVs = 20



(**f**) Intra-Route Algorithm: Patients = 50, UAVs = 20



(**g**) Inter-Route Algorithm: Patients = 50, UAVs = 20



(**h**) Tabu Algorithm: Patients = 50, UAVs = 20

Figure 8. Patient numbers and the UAVs utilized for two sample cases.

However, UAVs' legal challenges, users' privacy concerns, security threats to the UAVs, being prone to hacking, or a system fault causing sanitization failures, where the UAV may spread the virus rather than control it, are some issues that need to be looked at in the future. Nevertheless, the proposed system is a dynamic addition to the practical steps for curbing COVID-19 and similar viruses and moving towards smart health care systems. This can also be used to collect patients' urine and other samples, which do not require a medical specialist. In addition, these systems reduce carbon footprints and the associated air pollution as the deliveries are made through smokeless vehicles.

5. Conclusions

This study presented a hypothetical, sophisticated system for delivering COVID-19 self-testing kits to potentially infected patients and bringing the samples back to the testing centers to minimize the delivery and reception time as well as curbing the spread of the virus by minimizing the person-to-person contact. It uses AI to decide when delivering the test kits intelligently. Such sophisticated systems will help move towards smart healthcare. In addition, the reduced carbon footprints are the advantages of the proposed system, which are especially helpful for developing countries that struggle to control their carbon footprints due to the usage of outdated cars and delivery trucks.

The UAV paths are optimized using four key vehicle routing algorithms, greedy, intra-route, inter-route, and tabu algorithms, to reduce their flight time and optimize the distances. Four cases with 30, 50, 100, and 500 patients and subcases involving 10, 20, 30, 50, and 100 UAVs are investigated for delivering self-testing kits to the patients in Islamabad, Pakistan. The depot and UAVs launching ground are established in the PIMS hospital Islamabad, which is in central Islamabad. The results show that UAVs can be effectively used to deliver self-testing kits to potential patients, and the samples can be collected with ease without spreading the virus and minimizing the contact risks. Tabu shows the best results among the routing algorithms, covering an optimized distance of 31.85, 51.35, 85, and 349.15 km when a total of 30, 50, 100 and 500 patients are to be attended within the region, respectively. Tabu may not be the best alternative when computation speeds are the main concern; instead, inter-route and intra-route algorithms carry more speed advantages. However, in the current study, computation speed is not the main concern; hence, tabu is preferred as a routing algorithm.

The algorithms further optimize the number of UAVs to be used in each case: 30, 50, 100, and 500 patients are addressed with 5, 8, 14, and 71 UAVs, respectively. This highlights the limitation of the UAVs in the current study, where a single UAV can only cater to the needs of seven patients. This is mainly due to its limited battery power and testing kit handling capabilities. This can be addressed in the future using solar-powered larger UAVs capable of longer operations and more handling capabilities. Furthermore, these UAVs do not rely on sources that can increase the carbon footprints, thus reducing the air pollution generated by cars or delivery trucks.

Multiple variables limit the current study. First, the VRPTW technique of hybrid swarm intelligence is used, and others, such as the Chinese postman problem, are not considered. Second, the algorithms are restricted to four well-established algorithms, and as such, no new algorithm is developed. Third, some variables, such as wind speed and battery energy losses due to heat, are not considered. These can be considered by future studies to improve upon the current study and add more to the body of knowledge. Similarly, in the future, the legal implications, user's security, the hackability of the UAVs, maximum area coverage with minimum drones, performance optimization, fail cooperation probability between UAVs and patients as well as the astray probability of UAVs, and failure of the sanitization system of the UAV are potential risks or aspects that can be investigated.

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References

1. Worldometers. COVID-19 Coronavirus Pandemic. Available online: https://www.worldometers.info/coronavirus/?utm_campaign=homeAdvegas1?#countries (accessed on 24 October 2020).
2. Hasell, J.E.; Mathieu, D.; Beltekian, B.; Macdonald, C.; Giattino, E.; Roser, O.-O.M.; Ritchie, H. A cross-country database of COVID-19 testing. *Sci. Data* **2020**, *7*, 1–7. [CrossRef]
3. Liu, K.; Chen, Y.; Lin, R.; Han, K. Clinical features of COVID-19 in elderly patients: A comparison with young and middle-aged patients. *J. Infect.* **2020**, *80*, e14–e18. [CrossRef]
4. Homolak, J.; Kodvanj, I.; Virag, D. Preliminary analysis of COVID-19 academic information patterns: A call for open science in the times of closed borders. *Scientometrics* **2020**, *124*, 2687–2701. [CrossRef] [PubMed]
5. Smith, P. Covid-19 in Australia: Most infected health workers in Victoria's second wave acquired virus at work. *BMJ* **2020**, *370*. [CrossRef]
6. Zhu, S.; Wu, Y.; Zhu, C.-Y.; Hong, W.-C.; Yu, Z.-X.; Chen, Z.-K.; Chen, Z.-l.; Jiang, D.-G.; Wang, Y.-G. The im-mediate mental health impacts of the COVID-19 pandemic among people with or without quarantine managements. *Brain Behav. Immun.* **2020**, *87*, 56. [CrossRef]
7. Government of Pakistan. Pakistan Cases Details. Available online: http://covid.gov.pk/stats/pakistan?locale=en (accessed on 24 October 2020).
8. Farooq, F.; Khan, J.; Khan, M.U.G. Effect of Lockdown on the spread of COVID-19 in Pakistan. *arXiv* **2020**, arXiv:2005.09422.
9. Javaid, M.; Haleem, A.; Vaishya, R.; Bahl, S.; Suman, R.; Vaish, A. Industry 4.0 technologies and their applications in fighting COVID-19 pandemic. *Diabetes Metab. Syndr. Clin. Res. Rev.* **2020**, *14*, 419–422. [CrossRef] [PubMed]
10. Esmaeili, S.; Tabbakh, S.R.K.; Shakeri, H. A priority-aware lightweight secure sensing model for body area networks with clinical healthcare applications in Internet of Things. *Pervasive Mob. Comput.* **2020**, *69*, 101265. [CrossRef] [PubMed]
11. Ke, Y.-Y.; Peng, T.-T.; Yeh, T.-K.; Huang, W.-Z.; Chang, S.-E.; Wu, S.-H.; Hung, H.-C.; Hsu, T.-A.; Lee, S.-J.; Song, J.-S. Artificial intelligence approach fighting COVID-19 with repurposing drugs. *Biomed. J.* **2020**, *43*, 355–362. [CrossRef] [PubMed]
12. Alimadadi, A.; Aryal, S.; Manandhar, I.; Munroe, P.B.; Joe, B.; Cheng, X. Artificial intelligence and machine learning to fight COVID-19. *Physiol. Genom.* **2020**, *52*, 200–202. [CrossRef]
13. Ting, D.S.W.; Carin, L.; Dzau, V.; Wong, T.Y. Digital technology and COVID-19. *Nat. Med.* **2020**, *26*, 459–461. [CrossRef]
14. Ullah, F.; Sepasgozar, S.M.; Wang, C. A systematic review of smart real estate technology: Drivers of, and barriers to, the use of digital disruptive technologies and online platforms. *Sustainability* **2018**, *10*, 3142. [CrossRef]
15. Kumar, A.; Gupta, P.K.; Srivastava, A. A review of modern technologies for tackling COVID-19 pandemic. *Diabetes Metab. Syndr. Clin. Res. Rev.* **2020**, *14*, 569–573. [CrossRef] [PubMed]
16. Ullah, F.; Sepasgozar, S.M.; Shirowzhan, S.; Davis, S. Modelling users' perception of the online real estate platforms in a digitally disruptive environment: An integrated KANO-SISQual approach. *Telemat. Inform.* **2021**, *63*, 101660. [CrossRef]
17. Ullah, F.; Sepasgozar, S.M.; Thaheem, M.J.; Al-Turjman, F. Barriers to the digitalisation and innovation of Australian Smart Real Estate: A managerial perspective on the technology non-adoption. *Environ. Technol. Innov.* **2021**, *22*, 101527. [CrossRef]
18. Ullah, F.; Sepasgozar, S.M.; Thaheem, M.J.; Wang, C.C.; Imran, M. It's all about perceptions: A DEMATEL approach to exploring user perceptions of real estate online platforms. *Ain Shams Eng. J.* **2021**, in press. [CrossRef]
19. Hildmann, H.; Kovacs, E. Using Unmanned Aerial Vehicles (UAVs) as Mobile Sensing Platforms (MSPs) for Disaster Response, Civil Security and Public Safety. *Drones* **2019**, *3*, 59. [CrossRef]
20. Qadir, Z.; Ullah, F.; Munawar, H.S.; Al-Turjman, F. Addressing disasters in smart cities through UAVs path planning and 5G communications: A systematic review. *Comput. Commun.* **2021**, *168*, 114–135. [CrossRef]
21. Munawar, H.S.; Ullah, F.; Qayyum, S.; Khan, S.I.; Mojtahedi, M. UAVs in Disaster Management: Application of Integrated Aerial Imagery and Convolutional Neural Network for Flood Detection. *Sustainability* **2021**, *13*, 7547. [CrossRef]
22. Ullah, F.; Samad Sepasgozar, P.; Ali, T.H. Real estate stakeholders technology acceptance model (RESTAM): User-focused big9 disruptive technologies for smart real estate management. In Proceedings of the 2nd International Conference on Sustainable Development in Civil Engineering (ICSDC 2019), Jamshoro, Pakistan, 5–7 December 2019.
23. Qayyum, S.; Ullah, F.; Al-Turjman, F.; Mojtahedi, M. Managing smart cities through six sigma DMADICV method: A review-based conceptual framework. *Sustain. Cities Soc.* **2021**, *72*, 103022. [CrossRef]
24. Ullah, F.; Al-Turjman, F. A conceptual framework for blockchain smart contract adoption to manage real estate deals in smart cities. *Neural Comput. Appl.* **2021**, 1–22. Available online: https://link.springer.com/article/10.1007%2Fs00521-021-05800-6#citeas (accessed on 30 July 2021).
25. Ullah, F.; Qayyum, S.; Thaheem, M.J.; Al-Turjman, F.; Sepasgozar, S.M. Risk management in sustainable smart cities governance: A TOE framework. *Technol. Forecast. Soc. Chang.* **2021**, *167*, 120743. [CrossRef]
26. Tsouros, D.C.; Bibi, S.; Sarigiannidis, P.G. A review on UAV-based applications for precision agriculture. *Information* **2019**, *10*, 349. [CrossRef]

27. Nikitas, A.; Michalakopoulou, K.; Njoya, E.T.; Karampatzakis, D. Artificial intelligence, transport and the smart city: Definitions and dimensions of a new mobility era. *Sustainability* **2020**, *12*, 2789. [CrossRef]
28. Sethuraman, S.C.; Vijayakumar, V.; Walczak, S. Cyberattacks on healthcare devices using unmanned aerial vehicles. *J. Med. Syst.* **2020**, *44*, 9. [CrossRef] [PubMed]
29. Mukhopadhyay, A.; Ganguly, D. FANET based Emergency Healthcare Data Dissemination. In Proceedings of the 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 15–17 July 2020.
30. Euchi, J. Do drones have a realistic place in a pandemic fight for delivering medical supplies in healthcare systems problems. *Chin. J. Aeronaut* **2020**, *34*, 182–190. [CrossRef]
31. Hossain, M.S.; Muhammad, G.; Guizani, N. Explainable AI and mass surveillance system-based healthcare framework to combat COVID-I9 like pandemics. *IEEE Netw.* **2020**, *34*, 126–132. [CrossRef]
32. Wazid, M.; Bera, B.; Mitra, A.; Das, A.K.; Ali, R. Private blockchain-envisioned security framework for AI-enabled IoT-based drone-aided healthcare services. In Proceedings of the 2nd ACM MobiCom Workshop on Drone Assisted Wireless Communications for 5G and Beyond, London, UK, 25 September 2020.
33. Siriwardhana, Y.; Gür, G.; Ylianttila, M.; Liyanage, M. The role of 5G for digital healthcare against COVID-19 pandemic: Opportunities and challenges. *ICT Express* **2020**, *7*, 244–252. [CrossRef]
34. Ullah, H.; Nair, N.G.; Moore, A.; Nugent, C.; Muschamp, P.; Cuevas, M. 5G communication: An overview of vehicle-to-everything, drones, and healthcare use-cases. *IEEE Access* **2019**, *7*, 37251–37268. [CrossRef]
35. Ullah, F.; Al-Turjman, F.; Qayyum, S.; Inam, H.; Imran, M. Advertising through UAVs: Optimized path system for delivering smart real-estate advertisement materials. *Int. J. Intell. Syst.* **2021**, *36*, 3429–3463. [CrossRef]
36. IQAir. Air Quality and Pollution City Ranking. Available online: https://www.iqair.com/world-air-quality-ranking (accessed on 15 February 2021).
37. Lee, I.; Wang, C.-C.; Lin, M.-C.; Kung, C.-T.; Lan, K.-C.; Lee, C.-T. Effective strategies to prevent coronavirus disease-2019 (COVID-19) outbreak in hospital. *J. Hosp. Infect.* **2020**, *105*, 102. [CrossRef] [PubMed]
38. Buja, A.; Paganini, M.; Cocchio, S.; Scioni, M.; Rebba, V.; Baldo, V. Demographic and socio-economic factors, and healthcare resource indicators associated with the rapid spread of COVID-19 in Northern Italy: An ecological study. *PLoS ONE* **2020**, *15*, e0244535. [CrossRef] [PubMed]
39. Hussain, R.; Dawoud, D.M. Drive-thru pharmacy services: A way forward to combat COVID-19 pandemic. *Res. Soc. Adm. Pharm.* **2020**, *17*, 1920–1924. [CrossRef]
40. Nagura-Ikeda, M.; Imai, K.; Tabata, S.; Miyoshi, K.; Murahara, N.; Mizuno, T.; Horiuchi, M.; Kato, K.; Imoto, Y.; Iwata, M. Clinical evaluation of self-collected saliva by RT-qPCR, direct RT-qPCR, RT-LAMP, and a rapid antigen test to diagnose COVID-19. *J. Clin. Microbiol.* **2020**. [CrossRef]
41. Nomad. Coronavirus-Antibody-Self-Test-Kits. Available online: https://www.nomadtravel.co.uk/travel-store/coronavirus/coronavirus-antibody-self-test-kits (accessed on 24 October 2020).
42. Johns Hopkins Medicine. Self-Test for COVID-19: Instructions and FAQs. Available online: https://www.hopkinsmedicine.org/coronavirus/self-test.html (accessed on 24 October 2020).
43. Kroger Health. COVID-19 Test Home Collection Kit. Available online: https://www.fda.gov/media/139682/download (accessed on 24 October 2020).
44. Administration, T.G. Legal Supply of COVID-19 Test Kits. Available online: https://www.tga.gov.au/legal-supply-covid-19-test-kits (accessed on 23 October 2020).
45. Çodur, M.K.; Yılmaz, M. A time-dependent hierarchical Chinese postman problem. *Cent. Eur. J. Oper. Res.* **2020**, *28*, 337–366. [CrossRef]
46. Deng, W.; Xu, J.; Zhao, H. An improved ant colony optimization algorithm based on hybrid strategies for scheduling problem. *IEEE Access* **2019**, *7*, 20281–20292. [CrossRef]
47. Gutierrez, A.; Dieulle, L.; Labadie, N.; Velasco, N. A multi-population algorithm to solve the VRP with stochastic service and travel times. *Comput. Ind. Eng.* **2018**, *125*, 144–156. [CrossRef]
48. Munawar, H.S. Flood Disaster Management: Risks, Technologies, and Future Directions. In *Machine Vision Inspection Systems: Image Processing, Concepts, Methodologies and Applications*; Wiley: Hoboken, NJ, USA, 2020; Volume 1, pp. 115–146.
49. Gocken, T.; Yaktubay, M. Comparison of different clustering algorithms via genetic algorithm for VRPTW. *Int. J. Simul. Model* **2019**, *4*, 574–585. [CrossRef]
50. Zhou, Z.; Ma, X.; Liang, Z.; Zhu, Z. Multi-objective multi-factorial memetic algorithm based on bone route and large neighborhood local search for VRPTW. In Proceedings of the 2020 IEEE Congress on Evolutionary Computation (CEC), Glasgow, UK, 19–24 July 2020.
51. Shen, Y.; Liu, M.; Yang, J.; Shi, Y.; Middendorf, M. A hybrid swarm intelligence algorithm for vehicle routing problem with time windows. *IEEE Access* **2020**, *8*, 93882–93893. [CrossRef]
52. Dong, W.; Zhou, K.; Zhang, G.; Chao, H.-C. Modified discrete glowworm swarm optimization algorithm based on time window division for multi-objective vrptw. *J. Internet Technol.* **2018**, *19*, 001–013.
53. Mat, N.A.; Benjamin, A.M.; Abdul-Rahman, S.; Wibowo, A. Nearest greedy for solving the waste collection vehicle routing problem: A case study. In *AIP Conference Proceedings*; AIP Publishing LLC: Langkawi, Malaysia, 2017.

54. Mourad, B.; Chacher, A.A.; Cyril, F.; Hayder Ibrahim, H. Ontology-Based Reasoning System for Logistics Applications Deployment. In Proceedings of the Smart Application and Data Analysis for Smart Cities (SADASC'18), Casablanca, Morocco, 27–28 February 2018.
55. Montané, F.A.T.; Galvao, R.D. A tabu search algorithm for the vehicle routing problem with simultaneous pick-up and delivery service. *Comput. Oper. Res.* **2006**, *33*, 595–619. [CrossRef]