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A SIMULATION-HEURISTIC APPROACH TO OPTIMALLY DESIGN DRONE DELIVERY SYSTEMS IN RURAL AREAS

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ABSTRACT

In recent years, drone delivery has become one of the most widely adopted emerging technologies. Under the current Covid-19 pandemic, drones greatly improve logistics, especially in rural areas, where inefficient road networks and long distances between customers reduce the delivery capacity of conventional ground vehicles. Considering the limited flight range of drones, charging stations play essential roles in the rural delivery system. In this study, we utilize simulation to optimize the drone delivery system design, in order to minimize the cost of serving the maximum capacity of customers. As facility siting is usually difficult to optimize, we propose a novel simulation-heuristic framework that continuously improves the objective to find near-optimal solutions. In addition, we conduct a case study using real-world data collected from Knox County, Tennessee. The results suggest that the proposed approach saves over 15% on total costs compared with the benchmark.

1 INTRODUCTION

The past decade has witnessed the rapid growth of drones and autonomous systems that have become more capable. The technology needed to implement and maintain a drone delivery system has only been possible since the creation of microprocessors. Drone delivery systems stemmed from the inefficiencies of trucks within the last mile of the supply chain. The last mile of delivery is the most costly portion of the supply chain for all delivery companies. To solve this problem, commercial companies, such as Amazon (CBS News 2013), DHL (Discover Delivered by DHL 2022), Google (Koetsier 2021), and FedEx (FedEx 2019), are looking at drones as a viable source of package transportation. As technology continues to climb at an exponential rate, many supply chains have started to experiment with drone delivery systems. Major distributors like Amazon and Walmart are planning to implement such systems (Pandit and Poojari 2014). These systems could quickly change the overall profitability and efficiency of the last-mile delivery.

Drones have now been proven capable of successfully delivering lightweight packages. However, the implementation of drone delivery systems has met great difficulties in recent years, as many of these ventures have become stalled because of Covid-19 (Gao et al. 2021). The pandemic has demonstrated particularly severe impacts on rural areas, since rural residents live farther away from utilities than urban residents. As a result, drone delivery systems are growing to be more critical in rural communities throughout the U.S. (Brems et al. 2006). For example, under a healthcare context, a drone delivery system provides service to people who cannot access proper treatment, medication, and other lifesaving items on a consistent basis

(Brems et al. 2006). Also, in rural areas, patients are spread out in a large area, making conventional deliveries (via trucks) inefficient. In rural areas, truck drivers may only make a few drop-offs considering the distance between customers and the less industrialized terrain. This has an impact on the environment as well as the timeliness of the delivery. Within the healthcare profession, such difficulty is partly relieved by virtual doctor appointments (Health Resources and Services Administration 2021). However, this only solves a portion of the problem in rural communities because once a doctor has prescribed the medication, many patients still have to drive long distances to pick up the prescription. Elderly patients, injured people, or people on bed rest are often unable to receive their prescriptions because of transportation obstacles. This, in turn, leads to a lack of healthcare for individuals and induces life-threatening events (Health Resources and Services Administration 2021). Under the current Covid-19 pandemic, there are great opportunities to be explored in implementing drone delivery systems in rural areas.

2 Related Work

In the literature, there have been many drone delivery methods. One of the most well-studied methods, in both urban and rural, is the drone-truck system (Murray and Chu 2015). In this system, drones are placed in delivery trucks. Once the trucks arrive at destinations, the drones can be released to make one or more deliveries (Ulmer and Thomas 2018). When deliveries are completed, the drones would go to a designated location along the truck's route for pickup. Review papers and surveys have summarized research progresses and trends for this novel delivery method (Macrina et al. 2020; Moshref-Javadi and Winkenbach 2021). To complete the delivery, drones will be equipped with new batteries or charged after each sortie. However, frequently replacing or charging batteries could increase the time to deliver and cause negative environmental impact (Ferrandez et al. 2016). The truck-drone method also may not be the optimal solution for rural implementations (Marinelli et al. 2018), since it does not immediately resolve the problems that trucks travel inefficiently in rural road networks, and the flight range of drones only allows limited customers to be served.

Another system has shown great promises for drones to operate over long distances, with the assistance of charging stations in the area of service (Mourgelas et al. 2020). Kim and Lim (2018) proposed a drone surveillance network along the U.S. and Mexican border. This system introduces charging stations along the route to increase the range of drones. In a second study, Hong et al. (2018) showed the effectiveness of charging stations. Charging stations significantly increase the range of the drones by nearly doubling the given battery capacity (Choi et al. 2016). Typically, two types of charging stations are considered. One on which drones land and recharge (stationary) (Shin et al. 2019), and another that drones fly through, without stopping, to charge the battery (dynamic) (Kim and Lim 2018) (Mourgelas et al. 2020). The stationary charging station provides more charging capacity, but takes more time. The stationary charging stations are considered in many drone delivery studies (Marinelli et al. 2018). In contrast, the dynamic charging station only partially charges the battery, since the drone remains in flight, but it also saves time, and is more flexible to design. Since the stationary and the dynamic charging stations have their own advantages, experiments from the literature show that a mixture of the two would achieve the most efficiency in prolonging drone flights (Kim et al. 2018).

With the help of charging stations, one of the major problems of rural delivery systems can be overcome, where the distance between locations is too large for drones to cover. In current applications, excessive delivery hubs are placed to cover the service area, which increases the investment greatly. For example, in healthcare, the drone delivery system for rural patients is designed to deliver low weight packages such as medicine (Kim et al. 2017; Scott and Scott 2018). To accomplish this, multiple delivery hubs or depots are set up in optimal locations where their zones of operations only slightly overlap. The drones are then dispatched to customers, dropping off medication or other cargo (Kim et al. 2017). A similar system was created for disaster relief, specifically considering the infrastructure in underdeveloped countries (Rabta et al. 2018). With advanced camera and positioning systems, drones can easily distinguish objects, such as picking out a house from trees within an apartment complex, which allows drones to perform delivery operations in precision. All in all, for rural areas, drone delivery remains one of the most viable options (Brunner et al. 2019).

In order to design a drone delivery system in a rural area, drone depots are often placed throughout a predefined graph/network (Cornuéjols et al. 1983). Depots are “warehouses”, which drones will be released from and returned to. These depots are stationary locations placed though out a community to increase the effective coverage area of the deliveries (Cornuéjols et al. 1983; Wu et al. 2006). Depots are the biggest and most costly portion of this potential network. To combat the high prices of depots, charging stations will be placed in strategic locations on the edge of the delivery range to extend the delivery distance without having to add more costly depots to the network (Cornuéjols et al. 1983). Charging stations cost considerably less than depots because they will not need as much infrastructure or land to become operative. As discussed, charging stations give drones a much larger delivery range, allowing drones to serve more customers. The benefits of combining drone depot and charging stations include reduced investment, increased drone flight range, and better coverage of customers, leading to an efficient, environmentally-friendly last mile of delivery method (Raj and Sah 2019). However, the challenges still remain on how to optimally design infrastructure to support drone delivery operations (Frachtenberg 2019).

In this study, the optimal placement of drone depots and charging stations involve facility location decisions, which have been extensively studied by the Operations Research community, where many have considered the problem difficult to optimize, especially for large-scale implementations (Owen and Daskin 1998; Snyder 2006). In practice, there are many stochastic parameters like uncertain flight range which may make it even harder. To improve the solution methodology, in this study, we propose a simulation-heuristic framework that harnesses the power of simulation to enhance the optimization capability of heuristic algorithms. Simheuristics is the hybridization of simulation techniques with metaheuristics, which can help deal with optimization problems in uncertain domains (Chica et al. 2020). This problem under study is a NP-hard problem and has stochastic parameters. When dealing with large-scale stochastic optimization problems, simheuristics is considered as a “first resort” method to help decision-makers get reasonable optimal solutions in quick succession. Specifically, we combine an agent-based simulation model with a genetic algorithm (GA) to find the optimal locations of drone depots and charging stations. In addition, we validate our proposed approach through a case study that uses real-world data collected from Knox County, Tennessee.

3 PROBLEM FORMULATION

In this section, we formulate the optimal placement problem of drone depots and charging stations using integer programming (IP). We then briefly discuss the complexity of the problem and potential obstacles in solving it exactly.

Specifically, we use $i \in M$ to represent customers. We place drone depots at candidate locations $j \in V$, and charging stations at locations $k \in W$. There are fixed costs A_j associated with each drone depot and B_k with each charging station. Drones, with limited flight range R, depart drone depots to serve customers. Drones are allowed to charge at charging stations so that the flight range can be extended to serve distant customers. We use variable U_k to denote the number of charging stations visited by a drone starting from the depot to the charging station k, including k. E.g., $U_k = 1$ means that k is the first station visited by the drone, implying that the distance between k to its nearest depot is within R.

To provide delivery service to customers in distant regions, we aim to set up drone depots and charging stations in optimal locations. Similar to the literature (Scaparra and Church 2008), we allow decision-makers to choose from candidate locations in order to serve as many customers as possible and keep total costs at the minimum. The notation of this model is summarized in Table 1. The objective function of the IP model minimizes the total cost, including the cost of setting up depots, charging stations and the penalty cost of those unserved customers. The IP model can be formulated as follows.

$$\min \quad \sum_{j=1}^{J} A_j X_j + \sum_{k=1}^{K} B_k Y_k + \sum_{i=1}^{F} c_i P_i \tag{1}$$

Table 1: Notation of the IP model.

Notation	Definition
Index	
i	Index of customers
j	Index of depots
k,l	Index of charging stations
Variables	
X_j	If there is a depot in location j, $X_j = 1$. Otherwise $X_j = 0$.
Y_k	If there is a charging station in location k, $Y_k = 1$. Otherwise $Y_k = 0$.
U_k	Number of visited charging stations when arriving at k, integer variable.
$C_{i,k}$	If customer i is served by drones through charging station k, $C_{i,k} = 1$. Otherwise $C_{i,k} = 0$.
$C_{i,j}$	If customer i is served by drones which starts from depot j, $C_{i,j} = 1$. Otherwise $C_{i,j} = 0$.
c_i	If customer i is served, $c_i = 1$. Otherwise $c_i = 0$.
$Z_{j,k}$	If charging station k can be serve by depot j, $Z_{j,k} = 1$. Otherwise $Z_{j,k} = 0$.
z_k	If this charging station is connected to a depot directly, $z_k = 0$. Otherwise $z_k = 1$.
$\rho_{k,l}$	If charging station k is connected to charging station l, $\rho_{k,l} = 1$. Otherwise $\rho_{k,l} = 0$.
Parameters	
F	The set of customers
V	The set of potential depots
W	The set of potential charging stations
$D_{i,j}$	The distance between node i and j, where j represents either a depot or a charging station
A_j	The cost of depot j
B_k	The cost of charging station k
P_i	The penalty cost of unserved customer i
R	The maximum travelling distance for each fully-charged drone

$$\text{s.t.} \quad \sum_{j=1}^{J} C_{i,j} + \sum_{k=1}^{K} C_{i,k} \geq 1 \qquad \forall\ i \in F \tag{2}$$

$$C_{i,j}R + c_i M \geq 2D_{i,j} \qquad \forall\ j \in V, i \in F \tag{3}$$

$$C_{i,k}R + c_i M \geq 2D_{i,k} \qquad \forall\ k \in W, i \in F \tag{4}$$

$$C_{i,j} \leq X_j \qquad \forall\ j \in V, i \in F \tag{5}$$

$$C_{i,k} \leq Y_k \qquad \forall\ k \in W, i \in F \tag{6}$$

In the IP model, Equation (2) means that most customers are reachable by the drone from a depot or a charging station. Equations (3) and (4) limit that if customer i does not exceed the service range of depot j or charging station k, the distance between i and j or k should be no more than $R/2$, since drones have to travel back to a depot/charging station after delivery. If customer i cannot be served by any depots, (3) and (4) make sure that $c_i = 1$ and it will get an extra penalty cost in the objective function. Equations (5) and (6) make sure that the customer has the probability to be served by drones from depot j or charging station k only when there is a facility. With respect to the length of the paper, other constraints such as those that govern the connection between charging stations and drone depots are not included here. A drone must travel from and return to a depot, so a charging station only functions when it is reachable by a drone from a depot. In addition, we let M be a very big number to control integer variables.

We use Gurobi 9.1.1 on a personal computer with an Intel 2.70 GHz CPU and an 8G memory and test the mathematical model by a random instance with 20 customers, 2 depots and 10 charging stations. The optimal solution is obtained within 1 second. However, when we increase the problem scale to 50 customers, 3 depots and 40 charging stations, it has still more than 10% gap after 3,600 seconds and the optimal solution is not obtained.

Overall, the optimization model is complex since all the variables are integer. As a result, feasible solutions to the model are scattered discontinuously and nonlinearly within a high-dimensional convex hull (Conforti et al. 2014). Thus, solving the model exactly requires branching and bounding techniques, whose computational complexities increase exponentially with the size of the problem. This suggests that even for problems with moderate sizes, commercial solvers such as Gurobi cannot produce good-quality solutions within a reasonable time period. To resolve this issue, in the following section, we consider alternative routes to optimize the problem.

4 THE SIMULATION-HEURISTIC APPROACH

As discussed, the IP model becomes difficult to solve in reasonable time frames, especially for large-scale implementations. In order to find good-quality solutions fast, we use heuristic algorithms as the optimization procedure. However, as shown in the IP model, the problem is regulated by multiple constraints, which imposes great obstacles on the heuristic algorithm when evaluating feasible solutions. Thus, in the following, we incorporate the heuristic algorithm into an agent-based simulation environment, where the solutions improved by the heuristic algorithm can be quickly and accurately evaluated, instead of solving a system of linear constraints with integer variables.

In addition, by creating an agent-based simulation environment, the model can be easily modified into various extensions. For example, as Cheng et al. (2020) indicates, the performance of drones is affected by multiple uncertain factors, such as weather, temperature, or air density. When uncertainties are incorporated into the model, the simulated environment offers a convenient yet robust approach to finding good-quality solutions.

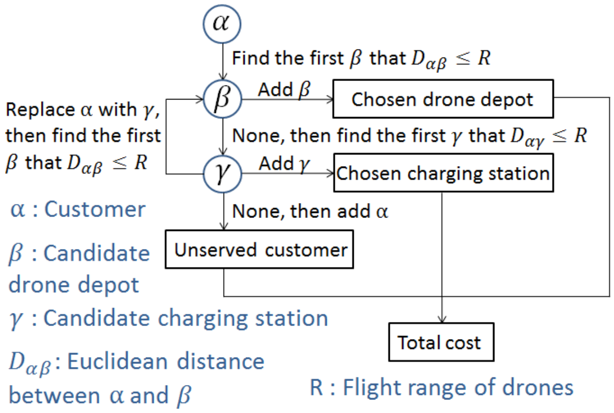
This model attempts to address a rural area similar to the population density of Sweetwater TN, where a major city (Knoxville) is within 40 minutes by car. This would attempt to help the underrepresented population of underprivileged individuals who do not have the opportunity to reach public health facilities. Many of these individuals are unable to reach the public health facilities because of lack of transportation. The public transportation is often too sparse, unreliable, and slow. They often times just can not take time off to take a day trip for there own health. This in part motivated us to study this problem.

Another reason for this study is to reduce the last mile of delivery, which is usually the most inefficient part of the supply chain. By directly servicing customers we reduce the carbon footprint and positively affect the environment. This is the case because trucks are needed for the last mile of delivery, which creates a higher carbon emission then drones. By introducing drones to the last mile of delivery in rural areas, less trucks will be needed as well as more customers can be served because trucks sometimes just can not reach a customer.

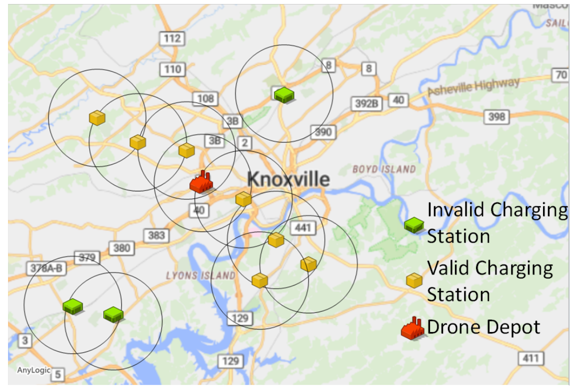
4.1 Agent-based Simulation

For this problem, we consider three types of agents: customers, charging stations, and drone depots. Drones themselves are not included as agents because the flight range of drones is modeled, on the high level, as the service range of drone depots and charging stations. The locations of customers, potential charging stations, and potential depots are modeled on a Geographic Information System (GIS) map according to their latitude and longitude. Since drones fly above terrains, we use the Euclidean distance to calculate the flight range between locations. The objective of the simulation model is similar to the objective of the IP model, with one distinction, where extra costs are added when customers are unable to receive service from drones, due to ill-placed depots or charging stations. The structure of the simulation model is shown in Figure 1.

In the simulation model, we call a charging station "valid", if and only if it is within the service range of another "valid" charging station or a depot. This means that a drone flying from a "valid" depot can reach any other "valid" charging station or depot. In addition, a customer is served when the customer lies within half of the service range of a "valid" charging station or a depot, so that a drone can fly to the customer and return for charging. The objective function is to minimize the aggregated costs of setting up



(a) The logic flow of an agent.



(b) An illustration of “valid” and “invalid” charging stations.

Figure 1: An overview of the agent-based model.

depots and charging stations, as shown in Figure 1a. Additionally, customers who are not “served” add additional penalty costs to the total cost.

Figure 1b illustrates “valid” and “invalid” charging stations. The yellow boxes represent the “valid” charging station which connects to at least one drone depot. The depot expands its service range by allowing drones to fly to charging stations. The green boxes represent the “invalid” charging stations, from which the flight range of drones cannot reach any depot, thus providing no benefits in serving customers. We are not sure which charging stations will be used to provide service when making decisions. So these “invalid” charging stations may be set up, but will not work in delivery.

Before the simulation, we initialize the agents and parameters. All the customers, depots and charging stations have parameters of their locations: longitude and latitude, which can be imported to AnyLogic GIS map. The drones have their own attributes like speed and flight range which can be chosen in a certain stochastic distribution. When simulating, the customers will find its closest depot. If the distance between a customer to its closest depot is no more than the flight radium of a drone, there will be a drone coming from that depot and delivering packages to that customer. Otherwise, the customer will find the first charging station which is in the service range of drones and continue to find the next charging station in the service range until there is a depot within the flight radium of the drone. If there is a customer who cannot find any depot to serve it, this customer is treated as unserved. Since our goal is to find the total cost of this delivery system, we compute the cost of building all the depots and charging stations which are used in serving these customers. Besides, there will be a penalty cost for each unserved customer in this delivery system.

4.2 Genetic Algorithm

The agent-based simulation creates an environment where the feasibility and optimally of the solutions are evaluated, which represents the decisions of the depot and charging station placements. In order to improve the solution, we incorporate a heuristic algorithm into the simulation environment. Specifically, we use GA as an optimization procedure to improve the solution quality.

Considering that our purpose is to choose some depots from a given depot set and choose some charging stations from a given charging station set, which can be seen as two decision lists with binary variables, we encode them as chromosomes and use GA to get a better solution. As a heuristic algorithm, GA provides some quick and relatively inexpensive feedback to decision-makers. And due to its high efficiency, we can use this algorithm multiple times with different random seeds to obtain better solutions. Moreover, GA can find satisfying solutions without changing the algorithm structure in different scenarios and it is much easier to be combined with simulation tools compared with other methods such as neural networks.

GA mimics the process of natural selection. GA starts with a population of chromosomes, which is the first generation. Each chromosome consists of multiple genes. Different chromosomes may perform differently in the environment. A fitness function can measure the quality of performance of each chromosome. Selected by the environment, the chromosome which performs better has a greater probability of producing offspring for the next generation, using a crossover operation. During the crossover, genes in the offspring's chromosome have probabilities to mutate, from which stronger individuals may emerge. The entire evolution process continues through multiple generations until a certain termination criterion is met.

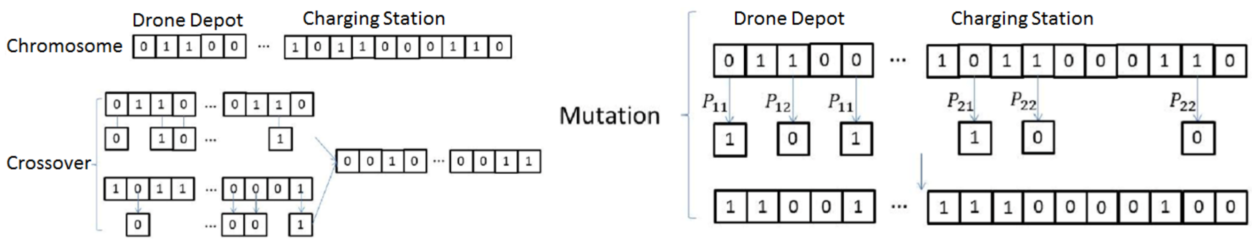


Figure 2: An illustration of the optimization process in GA.

In this problem, chromosomes represent binary decisions of whether to place a depot or charging station at a candidate location. A chromosome is encoded in such a way that the first part contains binary digits of depot locations, and the second part contains binary digits of charging station locations. Since our goal is to minimize the total cost of the drone delivery system, the fitness function is formulated by summing the cost of placed depots and charging stations. To acquire better solutions, GA allows the current population to "evolute", where crossover preserves the good genes in the current generation, and mutation introduces new possibilities for improvement. Specifically, in this problem, the parent chromosomes exchange part of the genes in the crossover. Mutation flips a binary digit in of gene from 0 to 1 or from 1 to 0.

Algorithm 1: Pseudo-code for GA.

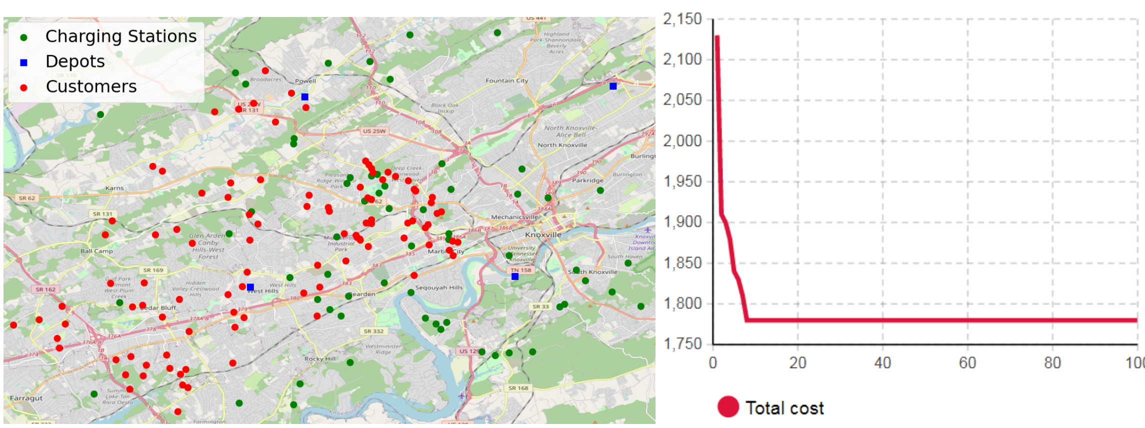
Initiate crossover rate C and mutation rate $P_{1,1}$, $P_{1,2}$, $P_{2,1}$, $P_{2,2}$
Initiate the minimal cost $T \leftarrow \infty$
Set all candidate locations of drone depots and charging stations to a queue D
Generate S random chromosomes as the population m_1 in generation $t \leftarrow 1$
while $t \leq M$ **do**
    Compute the fitness value of each chromosome in m_t
    Update the minimal fitness value T
    Record the chromosome R with minimal fitness value
    while The size of m_{t+1} not exceeds SC **do**
        Choose two chromosomes from m_t according to the fitness value
        Randomly exchange values in these two chromosomes and generate two new chromosomes
    end while
    The rest $S(1-C)$ chromosomes comes from m_t which have minimal fitness function
    for all Scan chromosome i in the m_{t+1} **do**
        for all Scan node j in i **do**
            j has a probability to change its value according to $P_{1,1}$, $P_{1,2}$, $P_{2,1}$ or $P_{2,2}$
        end for
    end for
    $t \leftarrow t+1$
end while
Output T and R

When implementing GA, we first initialize parameters, including population size (S), maximum generations (M), crossover rate (C) and mutation rate (P). Since drone depots are much more expensive than charging stations, we use different mutation rates for drone depot and charging station sections in a chromosome. Additionally, since most of the time, good solutions to the problem are scarce vectors, i.e., 0 digits appear more often than 1 digits, we further use different mutation rates when mutating 0 to 1 and mutating 1to 0. Specifically, the mutation rate of the drone depot section in a chromosome will have the probability $P_{1,1}$ of turning 1 to 0, and $P_{1,2}$ of turning 0 to 1, where $P_{1,1} > P_{1,2}$. The charging station section in a chromosome will have the probability $P_{2,1}$ of turning 1 to 0, and $P_{2,2}$ of turning 0 to 1, where $P_{2,1} > P_{2,2}$. Figure 2 concisely shows the optimization process of GA, where chromosomes go through crossover and mutation to produce better offspring. The pseudo code for GA is shown in Algorithm 1.

5 CASE STUDY

5.1 Data and Parameters

In this section, we conduct a case study to validate our method. Data used in this study were collected in Knox County, Tennessee, with the Google Maps API. Knox County features low-rise buildings and loosely packed residential homes, making it suitable as a case study for drone delivery in the rural area. We randomly select 101 customers in the area according to the United States Census Bureau (2021). Candidate depot locations are chosen according to 4 local UPS stores. We choose 67 candidate charging stations randomly using Census block data. Figure 3a illustrates the data, where red, blue, and green dots represent customers, candidate depots, and candidate charging stations.



(a) The map of customers and facilities. (b) The best objective in each generation of GA.

Figure 3: Data and results.

According to Kirschstein (2020), the flight range of a drone can be up to 9 km. Here we let the drone's flight range follow a uniform distribution from 4 to 8 km since the load and weather will consume more energy than no load in good weather. The setup cost of drone depot is estimated to be \$1 million (Greg Clinton 2022), and the cost of a charging station with 10 charging pads is estimated to be \$10,000 (Nick Lavars 2014). In this case study, to avoid numerical issues, we re-scale the costs, so that they become manageable for the simulation model. We let the cost of a depot be \$1 million, and the cost of a charging station be \$10,000. In addition, each customer who cannot receive service will cost extra \$100,000 as a penalty. To implement GA, we let $S = 100$, $M = 100$, $C = 0.75$, $P_{1,1} = 0.01$, $P_{1,2} = 0.1$, $P_{2,1} = 0.01$, and $P_{2,2} = 0.05$.

5.2 Results

To evaluate the performance of the simulation-heuristic framework, we include a greedy algorithm as the benchmark, which always looks for the solution with the lowest costs to serve the largest number of customers. Specifically, the greedy algorithm assigns each customer to the nearest selected depot, and connects the customer with the depot using the minimum number of charging stations.

We first show the results from GA. Figure 3b plots the total cost of the best drone delivery system design in each generation. Initially, the total cost of the drone delivery system is more than \$2.1 million. As the generation increases, better solutions are found. After 100 generations, the best solution found by the GA needs only one drone depot and one charging station, which cost only \$1.78 million in total. For each scenario, the greedy algorithm takes less than 0.1 seconds. And the running time of GA mainly depends on the population size and the number of iterations. In the case of more than 100 customers, the population size of 100 and 100 iterations, this algorithm only takes less than 2 minutes, which can be even faster if we reduce the maximum generations.

Table 2: Comparison between GA and the greedy algorithm.

Instance	Scenario 1		Scenario 2		Scenario 3	
Method	GA	Greedy	GA	Greedy	GA	Greedy
Total cost (\$1,000)	1,780	2,140	1,920	2,760	1,580	1,940
Drone depot	1	1	1	1	1	1
charging station	18	34	12	26	18	34
Unserved customers	6	8	7	15	4	6

Compared with the greedy algorithm, GA clearly outperforms. Table 2 shows the comparison between GA and the greedy algorithm in different scenarios. In scenario 1, we have 101 customers, 4 depots and 67 charging stations. There are 101 customers, 3 depots and 55 charging stations in scenario 2, and 80 customers, 4 depots and 67 charging stations in scenario 3. We can see that GA gets better solutions than the greedy method in each scenario with lower cost and more served customers. Besides, GA takes less than 2 minutes in all these experiments. Although the greedy algorithm can provide a solution in a very short time, GA provides significantly better solutions with the cost of an acceptable time. Moreover, these scenarios will be very hard to find the optimal solution by solvers since the scale is simply too large, which means this efficient heuristic algorithm is very helpful.

5.3 Sensitivity Analysis

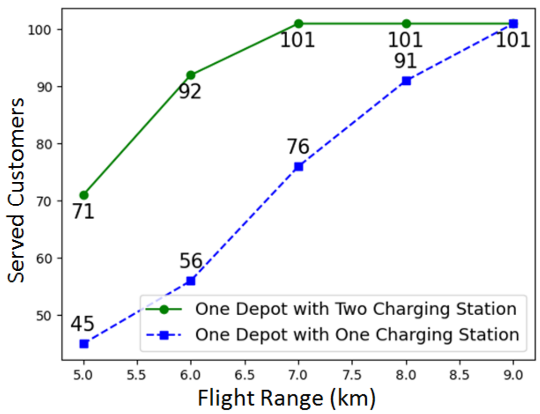
5.3.1 Drone Flight Range

In this section, we conduct additional experiments with varying drone flight ranges. Considering that the flight range of drones is affected by multiple factors (Cheng et al. 2020), we let the flight range of drones follow a uniform distribution from 6 to 9 km. We use the minimum, mean and maximum values for the flight range, as well as randomly sampling from the uniform distribution. Especially, when the uniform distribution is used, we report the average objective value of 10 repeated evaluations. Additionally, an extreme case is also conducted that the drones can only travel for 5 km, which is shorter than expected.

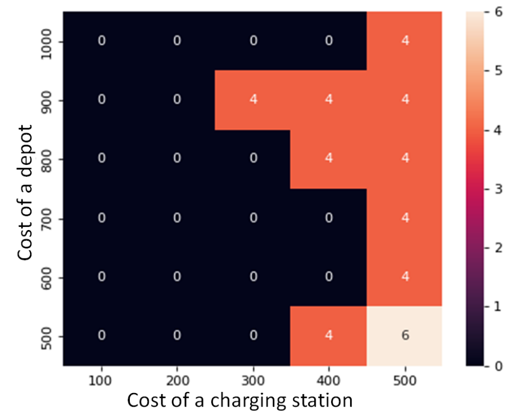
Table 3: Drone delivery system design with varying flight range.

Flight range (km)	5	6	7.5	9	Uniform Distribution
Total cost (\$1,000)	2,930	1,030	1,020	1,010	1,020
Drone depot	2	1	1	1	1
charging station	3	3	2	1	2
Serve customer	92	101	101	101	101

Table 3 shows the results of the experiments. In most cases, to serve all customers, one depot and two charging stations are needed. However, when the drones assume the maximum flight range, the results intuitively suggest that only one depot, as well as one charging station, is required. Overall, the experiments show that in the case of uncertain flight range, placing one drone depot with two charging stations can serve all customers in most cases. But when the flight range becomes extremely small, even two depots with three charging stations cannot serve all customers, which makes the delivery system based on the flight range between 6-9 km fail in this case. Additionally, when we assume that the flight range is always the maximum value, the best result we obtained will not do well if the flight range decreases. But the result in Random Uniform case still works well in different cases. Figure 4a shows how many customers will be served with two different drone delivery systems when the drones have various flight ranges.



(a) Number of served customers with shorter flight range.



(b) The number of unreachable customers with varying cost ratios.

Figure 4: Sensitivity analysis.

5.3.2 Facility costs

Considering that in practical situations, the construction cost of depots and charging stations may vary, according to numerous factors, such as location, technology, design, etc. (Greg Clinton 2022), we further conduct a sensitivity analysis on the costs of depots and charging stations, to provide insights for practitioners. Specifically, we vary the ratios between the cost of depot versus charging station, ranging from 10:1 to 1:1.

Results of the experiments are shown in Figure 4b, as the impact on customer coverage. Comparing the first two columns, the results show less sensitivity regarding charging station costs, as the model strives to serve all customers to avoid additional penalties. However, when the cost of charging stations increases, the behavior changes, where the model would rather sacrifice customer coverage, than pay for additional charging stations, due to the expensive cost. Overall, the results suggest that for practitioners, in order to maximize customer coverage, it is critical to control the price of charging stations, which are the keys to prolonging the drone flight range.

6 CONCLUSIONS

In this study, we consider a novel drone delivery system that optimizes the placement of drone depots and charging stations, prolonging the flight duration of drones, and thus expanding their customer-serving capabilities. To solve the problem, we first formulate an optimization model. Due to the difficulties in solving the optimization model, we propose a novel simulation-heuristic framework that incorporates heuristic algorithms into simulation environments. Specifically, we model the drone delivery problem with agent-based simulation and optimize the locations of drone depots and charging stations using GA.

To validate the model, we further conduct a case study that employs data collected from the real world. Results of the case study show that the simulation-heuristic framework produces solutions that save more than 50% on the cost compared with the greedy algorithm, with 100% customer coverage.

From a future research perspective, multiple types of drones can be considered, which may have different flight ranges. Optimization under this setting will impose more challenges. Additionally, impacts from the environmental factors should be studied, where a scenario-based or simulation-based model could improve system stability under uncertainties.

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