

# Future Demand and Optimum Distribution of Droneports

Yixi Zeng<sup>1</sup>, Kin Huat Low<sup>3</sup>, Michael Schultz<sup>2</sup>, and Vu N. Duong<sup>4</sup>

**Abstract**—Due to the growing usage of Unmanned Aerial Vehicles (UAVs, or drones) in commercial, civil, and military applications, thousands of drones are expected in the urban airspace for many decades to come. The large traffic volume of drones brings many concerns about safety issues especially during the taking-off, approaching, and landing phases when most accidents and incidents occur. In this paper, a facility called droneport is conceived to accommodate and manage assorted drones taking off and landing in a protected space under air traffic control. We present several contributions to the concept of droneport: (1) The future delivery drone demand was forecasted using historical online retailer data and the Holt-Winters’ seasonal method. (2) The optimum number and distribution of droneports were determined by a multi-objective optimization model considering both costs and societal value from six aspects: maximizing e-commerce demand coverage, airtaxi demand coverage, subzone coverage, and area coverage, and minimizing service distance for both parcel and passenger delivery drones. (3) The optimization model integrates Gaussian noise to make the measurement of service distance more practical. (4) The future capacity of each droneport was estimated based on the number of droneports and their placement. A real-world case study was carried out for Singapore. Overall, this paper presented an intuitive and efficient optimization model for the placement of droneports with predicted drone demand and forecasted the capacity of each droneport.

## I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs, commonly called drones) have attracted great attention in many areas, such as goods and passenger delivery, surveillance, search and rescue, sports events and agricultural monitoring, etc. Many private sector actors such as Amazon [1], Google [2], Uber [3], and DHL [4] have developed various projects on drone delivery. The feasibility of drone delivery is discussed based on its economic benefit and societal benefit [5], [6] and the analysis shows that drone delivery has high potential to be implemented in the future. However, as the drone delivery market grows rapidly, a large number of drones in lower airspace presents a serious hazard for other vehicles, people, industrial facilities, and the environment, especially in the highly populated urban areas [7]. Safety thus becomes a critical issue that must be addressed and regulated.

In a statistical analysis report done by wild et al.[8], a large proportion of the accidents and incidents of Remotely Piloted Aircraft System (RPAS), a subcategory of

the unmanned aircraft system (UAS), happened during take-off, landing and approach phases. Given a high occurrence possibility of accidents during those phases, we conceive a facility called droneport to manage different flight phases for drones considering thousands of daily operations and provide warehousing too. This idea is similar to the google patent filled-up by Amazon in 2017 [9], which describes a multi-level fulfillment center for drones. However, droneport can accommodate heterogeneous drones that are not limited to delivery drones and ensure the safe and expeditious flow of departing and approaching drones with the integration of air traffic control.

Similar to the airport, droneport provides facilities to store, maintain, and manage drones. Reliable technologies as well as regulations including air traffic flow management are its core of design. Each level of droneport contains take-off and landing pads used to charge drones, install/unload packages, and pick up/drop off passengers. Inside the droneport, navigation instruments are equipped to guide drones fly in or out of the building along a ‘taxiway’. While outside is a control zone (CTR), a safety perimeter of a droneport, providing protection to departing and approaching drones. Due to the intensive drone movement around the droneport and safety issues, warehouses with shelters are allocated in this CTR instead of residents or public infrastructure. Moreover, droneport has adjacent transport capacities to carry cargo or passengers from somewhere else to the droneport by trucks or taxis. Some operational concepts and technologies involved in the design of droneport have been investigated in Metropolis project [10].

To established urban areas such as Singapore, the questions raised are about where to distribute these droneports optimally with respect to potential demand of drone operations, and how many future capacities have to be faced by these droneports. In this paper, we first forecasted e-commerce demand in Singapore based on the Holt-Winters’ seasonal method [11]. Using this predicted number of online orders and airtaxi demand, we estimated the future demand of drones, as the forthcoming drone market will be mainly driven by delivery use. The optimization model consists of six objectives, which are (1) maximize e-commerce demand coverage, (2) maximize airtaxi demand coverage, (3) minimize parcel delivery drone service distance with Gaussian noise, (4) minimize service distance for airtaxi, (5) maximize subzone coverage, and (6) maximize area coverage. The first five objectives mainly serve for point to point missions, and the purpose of the last objective is for the area-based missions. This model aims to optimize droneports locations and thus determine an optimum number of droneports.

<sup>1</sup>Y. X. Zeng, <sup>3</sup>K. H. Low, and <sup>4</sup>V. N. Duong are with the Air Traffic Management Research Institute, Nanyang Technological University, Singapore 637460 {zeng0117, mkhlow, vu.duong}@ntu.edu.sg

<sup>2</sup>M. Schultz is with the Institute of Logistics and Aviation, Dresden University of Technology, 01069 Dresden, Germany michael.schultz@tu-dresden.de

The remainder of this paper is organized as follows. The next section provides an overview of the prior arts. Section 3 presents the location optimization model. A real-world case study carried out for Singapore is presented in Section 4, followed by the results of the optimized model in Section 5. Finally, the paper concludes with a discussion and outlook.

## II. LITERATURE REVIEW

Despite the increasingly common use of drones in our daily life, there are many technical challenges raising when operating drones to complete delivery or search missions. These include loading capacity and battery capacity. Commercial drones with payloads currently cannot achieve long-term missions without frequent set-up of recharging stations. Many researchers thus focus on the operational requirements for drone development, such as system scheduling and path planning with pre-determined recharging stations in disparate geographic locations [12], [13], and construction of infrastructure for drone delivery.

There are many private sector actors working on the infrastructure. Amazon proposed a multi-level fulfillment center for parcel delivery drones in 2017 [9]. This patent's viability was examined by Aurambout et al. [14] via investigating its economic potential in European urban areas. They emphasized that the setup of such fulfillment centers needs regulatory measures regarding drone flights and policy implications in the form of physical safety, air traffic management, and environmental aspects. Besides, Uber [3] has also considered this infrastructure as the precondition of its business model. They proposed a condition that the passenger delivery drones landing and taking off from vertiport and vertistop.

The infrastructure location problem for range constrained drone is of great interest to develop a new era where drones act as emerging transportation. The objective is to reduce the constructional cost and operational cost that are more closely related to this paper. For example, Hong et al. [15] developed models to locate the recharging stations which can help increase the demand coverage of drones. Some other studies have dealt with locations optimization for both recharging stations and warehouses. Shavarani et al. [16] evaluated the total cost of drone delivery based on a randomly generated demand from Poisson distribution and optimized both number and locations of recharging stations and warehouses in San Francisco.

Except for the increasing studies of allocating delivery facilities, some researches examine the optimum distribution of center locations for disaster relief operations. In [17], the last-mile distribution in the humanitarian logistics problem was formulated to find the optimum recharging stations considering drone constraints and disaster specific circumstances. Chauhan et al. [18] developed a formulation, Maximum Coverage Facility Location Problem with Drones (MCFLPD), to locate drone launching facilities.

Kellermann et al. [19] provide a detailed review of all papers on passenger and parcel delivery drones. It is no surprise that the facility location problems for drone delivery

systems emphasize economic benefits. However, in many operations such as search and rescue, the total cost should not be the only optimization target. Instead, area coverage might be particularly important, because a high level of geographic accessibility of drones can reduce total travel time and average lead time.

Different from the existing articles, this paper brings forward the idea of droneport that accommodates heterogeneous UAVs for a variety of applications, like delivery, agriculture, search and rescue, disaster relief, and surveillance. The optimization problem, therefore, is formulated considering not only the delivery mission but also surveillance mission. Moreover, a noise term is integrated modeling drone flight distance uncertainties between demand and droneports. It is more practical compared to existing works since drones are easily influenced by unexpected adverse weather conditions and physical obstacles and their flight path may change from the designed route suddenly.

## III. RESEARCH APPROACH

The goal of this paper is to find the optimum number of droneports and their geo-locations so that the capacity of each droneport can be determined. Our previous work constructed an optimization model mainly considering parcel delivery. In this section, heterogenous tasks performed by drones are classified into two types: point-point mission, including passenger delivery and package delivery; and area-based mission, consists of search and rescue, surveillance, and photography. An optimization problem is formulated based on these two types of missions. The objectives for this problem are two-fold: the first is to use an optimization algorithm and find the optimum distribution of droneports based on a pre-specific number of droneports, and the second is to obtain the optimum droneport number via comparing the value of three aspects.

### A. Mission Types

For the point-to-point mission, drones with parcels or passengers are launched from the droneports and drop the parcels or alight the passengers at the destinations. This type of mission spends negligible time at the destinations. The droneport coverage range thus depends only on drone battery constraints. As the economic benefit is addressed as important consideration for the stakeholders who work on drone delivery projects, the droneport is required to cover the most existing and potential demand leading to lower costs for companies. Moreover, service distance is also an optimization factor. Shorter service distance decreases drone battery consumption and, therefore, reduce drone usage costs.

For the area-based mission, drones are commanded to the desired location and conduct certain missions at that location. Usually, drones spend most of the energy and time on the mission instead of the trip. This type of mission includes search and rescue, surveillance, videoing, and agriculture monitoring, which would be conducted in any location. Consequently, area coverage is the most important concern.

## B. Optimization Model

Considering these two types of missions, the optimal locations of droneports can be obtained by maximizing existing and potential demand coverage and area coverage, and also minimizing accumulated service distance. Below is the formulated optimization model,

$$\begin{aligned} \max \quad & f(X, Y) = \sum_{k \in K} (\sigma_k * Q_k - \delta_k * D_k) + \eta * S + \phi * A \\ \text{s.t.} \quad & 1) d_{ip} > r, i = 1 \dots N, p = 1 \dots N \\ & 2) \text{ droneport network connectivity} \end{aligned} \quad (1)$$

where  $x_i \in X$  and  $y_i \in Y$ .  $x$  and  $y$  are the Universal Transverse Mercator (UTM) coordinates of droneports and subzones in meters.  $d_{ip}$  is the Euclidean distance between droneport  $i$  and droneport  $p$ .  $K$  is set of point to point mission considered in this model, and  $N$  is the pre-defined number of droneports. Four terms  $Q$ ,  $D$ ,  $S$ , and  $A$  represent demand coverage, service distance, subzone coverage, and area coverage respectively. The model is a weighted sum of these terms with four factors  $\sigma, \delta, \eta$ , and  $\phi$ .

**Demand coverage.** This term is intended to evaluate the proportion of demand covered by all droneports.

$$Q = \sum_i^N \sum_j^M \left[1 - \frac{d_{ij}^2}{r^2}\right]_+ * q_j \quad (2)$$

where  $M$  is the total number of subzones and  $q_j$  is the proportion of demand of subzone  $j$ . Subzone is the planning area delineated by a country or city and its resident population can be collected from a reliable source. Each subzone is served by a town center and several neighborhood commercial centers.  $\left[1 - \frac{d_{ij}^2}{r^2}\right]_+$  is the hinged ceiling function. Acting as a mask term, it becomes 1 if subzone  $j$  is covered by droneport  $i$  while 0 if subzone  $j$  is not covered by droneport  $i$ .  $r$  is the maximum radius that a delivery drone can travel and  $d_{ij}$  is the Euclidean distance between droneport  $i$  and subzone  $j$ .

**Service distance.** This term is defined to measure total service distance, which can be calculated as the weighted sum of the distance from every droneport and subzones within.

$$D = \sum_i^N \sum_j^M \left[1 - \frac{d_{ij}^2}{r^2}\right]_+ * \frac{h_{ij}^2}{r^2} \quad (3)$$

where  $h_{ij}$  calculates the dynamic flight distance by applying a Gaussian noise to the Euclidean distance  $d_{ij}$ ,

$$h_{ij} = \sum_k^{q_j W} W * \|(x_i, y_i) - (x_j^k, y_j^k)\|_2 \quad (4)$$

where  $W$  is the total demand,  $x_j^k \in x_j'$  and  $y_j^k \in y_j'$  follows a 2-dimensional circular Gaussian distribution defined as below,

$$g(x_j', y_j') = \frac{1}{2\pi\sigma_j^2} e^{-\frac{(x_j' - x_j)^2 + (y_j' - y_j)^2}{2\sigma_j^2}} \quad (5)$$

The variance  $\sigma_j^2$  is calculated based on the area of subzone  $j$ . More specifically, a circle that has the same area as the corresponding subzone is generated, and its radius is used to determine the variance  $\sigma_j^2$ . The integration of the Gaussian noise in this term makes the calculated flight distance closer to real traveled distance. In practice, drone flight distance does not strictly equal to the Euclidean distance because of the impact of crosswind, physical obstacle, or other changes in the environment. This paper assumes that the destination of drone delivery locates in the center of a subzone, thus Gaussian noise is chosen to model the distance variance. However, a different noise can be applied to other scenarios. For example, a uniform noise might be a better choice if it is doorstep delivery, as family houses are more likely to follow a random distribution within the belonged subzones.

Besides, the distance is not directly applied as part of the energy term, because the distance is a large number comparing to the proportion of demand term. As a result, a normalized service distance  $h_{ij}/r^2$  is used. The inclusion of  $q_j$  in the  $h_{ij}$  helps to count the number of trips between a droneport and its subzones, assuming that each drone carries one package.

**Subzone coverage.** Similar to the previous two terms, this term also serves for point to point delivery mission. However the demand and destinations of some tasks are not able to be predicted. Hence, it is necessary to cover subzones with zero demand and include this objective in our model. To measure the percentage of subzones covered by all droneports, we use the mask term  $\left[\sum_i^N \left[1 - \frac{d_{ij}^2}{r^2}\right]_+ / N\right]_+$  to tally the covered subzones.

$$S = \sum_j^M \left[\frac{1}{N} \sum_i^N \left[1 - \frac{d_{ij}^2}{r^2}\right]_+ \right]_+ * \frac{1}{M} \quad (6)$$

**Area coverage.** When optimizing droneport locations for area-based mission, area coverage should be considered as one of the most important factors. Different from subzone coverage, area coverage not only counted the mainland but also the sea.

The objective function is subjected to certain hard constraints enforcing the final algorithm to be efficient and effective. First, restricting the overlap between each pair of droneports can speed up the optimization process and filter out undesired solutions. Second, ensuring connected droneport network makes sure that there is at least one path from any droneports to any other droneports in this network. Since a drone has a limited endurance, if a fully charged drone can fly from one droneport to another droneport, then a link will be assigned between these two droneports.

For the second hard constraint, proving network connectivity is in nature an intricate nonlinear problem, which makes this optimization problem non-convex. This optimization problem aims to find a set of Pareto-optimal solutions,

meaning none of the objective functions can be improved without degrading some of the other objective values. Thus, we solve it using an NSGA-II (Non-dominated sorted genetic algorithm) solver. NSGA-II is a stochastic evolutionary multi-objective algorithm that can solve a multi-objective optimization. After optimization, a set of geo-coordinates for  $N$  droneports is obtained.

#### IV. CASE STUDY

Singapore has an area of  $725.1 \text{ km}^2$  and a population of around 5.7 million, and it is selected for the case study. Singapore can be divided into 323 subzones where each of them has a demand density as shown in Fig. 1. The data of total e-commerce demand in 2019 for Singapore was estimated from Statista Portal [20], Shopee annual report [21] and Amazon [22]. No survey and study show the e-commerce demand distribution in Singapore, and thus the population distribution [23] is used as a reference. We assume that these two types of data are following the same distribution. The map applied in area-based mission is enclosed by blue line in Fig. 1 [24].

The droneport operation coverage for point to point mission is constrained by the delivery drone's maximum travel range. As proposed in Amazon's Prime Air project in 2019, a parcel delivery drone is going to have a range of 24 km and less than 30 minutes respectively with a payload under 2.3kg [25]. However, this distance is measured under a straight flight in mid-air. In real life, the drone may hover, turn, climb, or descent due to changes in surroundings, and the residual battery should be kept above 15% due to safety issues. After taking those uncertainties into consideration, the droneport coverage was set to be 10 km based on Murray and Raj's numerical analysis [26], in which 10 km is defined as a high-range drone carrying a 2.3 kg parcel. The range for passenger delivery drone is set to 35 km referring to Volocopter [27]. As for area-based mission, the droneport coverage range depends on the drone's traveling time from droneport to mission location. Normally, a surveillance drone has a fly range of around 100 km [28]. In this research, we set a threshold of 30%, which means that drone consume at most 30% battery on traveling and at least 70% battery left to complete mission.

In this case study, we don't block out restricted, dangerous, protected, and prohibited areas in Singapore. Since there will be a need to cover those areas under droneport, as specific drones may be allowed to fly in those areas in the future.

#### V. RESULTS AND ANALYSIS

##### A. Drone Demand Forecast

We extracted available historical data of Amazon net quarterly revenue from 1st quarter 2007 to 4th quarter 2019, Amazon active customer accounts from 1st quarter 2013 to 2nd quarter 2016, Amazon average number of orders per customer, Shopee gross orders from 3rd quarter 2016 to 3rd quarter 2019 and Shopee quarterly gross merchandise value (GMV) from 3rd quarter 2016 to 3rd quarter 2019. All data listed above are worldwide data. The average order

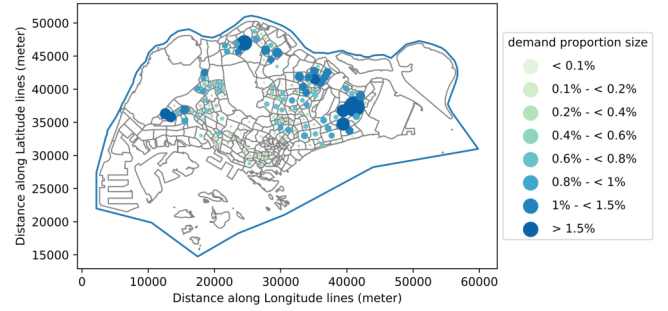


Fig. 1. Demand distribution in Singapore in 2019 (150 million orders  $\approx$  0.4 million orders per day).

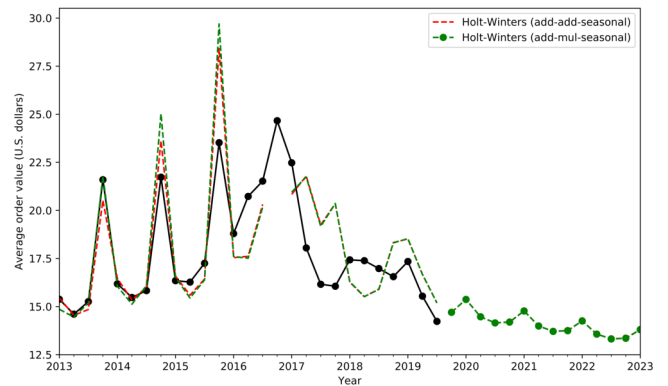


Fig. 2. Average order value (AVO) forecast from Holt-winters seasonal method.

value (AOV), meaning the average dollar amount spent by customer in an online order, therefore was calculated based on these data. We found a trend and seasonality exhibiting in the AOV, so we adapted the Holt-Winters seasonal method to predict the AOV for 2020-2022, shown in Fig. 3.

Although the data is insufficient, the trend and seasonality of AOV are obvious. The slowly descending of trend of the predicted AOV visible in Fig. 3 may be due to the increasing popularity of online shopping. In recent years, people buy online products more frequently. The disconnected point of fitted lines appears around the joint of Amazon data and Shopee data, which reveals the different customer behavior of these two companies. Combing annual AOV and total e-commerce revenue in Singapore [20], we can predict the number of orders from 2020 to 2022 (Table I).

A more accurate prediction can be achieved if more data with a longer period from three or more online retailers are provided. Nonetheless, the Holt-winters seasonal method is a simple and effective way to forecast delivery drone demand.

Demand forecast for passenger delivery drone is much more complex than parcel delivery. In this case, we use the average ridership data for taxi as an estimation. In Singapore, the taxi ridership almost maintained at 0.954 million annually, regarding the period from 2001 to 2015 [29].

TABLE I  
ESTIMATED ONLINE ORDERS IN SINGAPORE USING THE HOLT-WINTERS  
SEASONAL METHOD

Year	Total revenue (million US\$)	AOV (US\$)	Total orders (millions)
2020	2784	14.49	192.1
2021	3216	13.99	229.9
2022	3516	13.59	258.7

### B. Optimization Results

The optimization algorithm proposed in section 3 was implemented in Python 3 and the solver was constructed using the Platypus library [30]. It is intuitive that service distance is proportional to demand coverage, because service distance counts for cumulative travel distance for all delivery drones, and its number depends on e-commerce. However, one of the objectives of the optimization model is to maximize demand coverage at the same time minimize the service distance. Consequently, tuning weight parameters  $\sigma$  and  $\delta$  gains significance to achieve this balance. In this paper, we only consider parcel delivery and passenger delivery in point to point mission type, so six parameters  $\sigma_1, \sigma_2, \delta_1, \delta_2, \eta$ , and  $\lambda$  were tuned via 5 runs for 4 different  $N$  (6, 7, 8, 9). Left-tailed Wilcoxon Signed Rank Test was conducted to compare the performance of different sets of weight parameters, and the combination of 1.25, 0.2, 1, 0.1, 1, and 0.3 surpasses among all sets in demand coverage, service distance, subzone coverage, and area coverage. Experiments show that parameter tuning takes an important role in this optimization. An unsuitable set of parameters would reflect on the optimization performance. For example, a combination of 3, 0.2, 2.6, 2.6, 2.6, and 0.1 gave a result of around 46% demand coverage, 50% subzone coverage, and 75% area coverage.

We first examined the properties of optimum solutions given by the optimization algorithm. NSGA-II is a heuristic algorithm and it cannot guarantee a global optimum solution. Hence, five repeated runs were carried out for each  $N$  and the solution with the best fitness value is summarized in Table II. We then compared the optimization performance

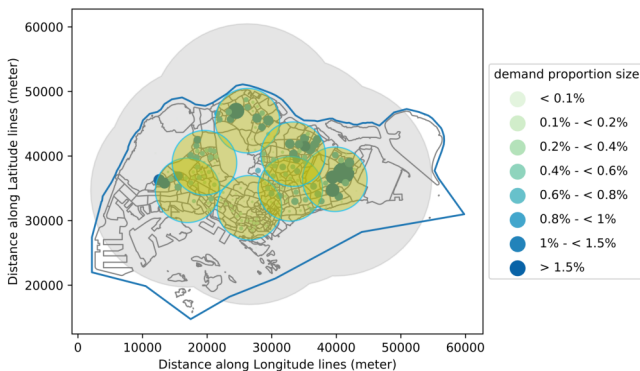


Fig. 3. Spatial distribution of 7 droneports in Singapore resulting from the optimization model

of different  $N$ . There is a significant improvement in three coverage values between 6 droneports and 7 droneports. However, the service distance increases with larger droneport number. Intuitively, 7 droneports cover more demand than 6 droneports, thus more service distance is counted in. Comparing 7 droneports and 8 droneports, build one more droneport only increase a little in the three coverage values. From economic viability aspect, a possible way is building 7 droneports and several charging stations. Fig. 3 illustrates the spatial distribution of 7 droneports in Singapore. The light grey shadow depicts operational range for all droneports under surveillance mission. Table. III lists all candidate facility locations and their capacities.

In conclusion, our optimization model is capable of finding the optimum number of droneports as well as their geo-locations. By assessing both fitness value and three energy terms, we recommend that 7 droneports should be chosen in the case study of Singapore.

## VI. CONCLUSIONS

This paper introduced droneport, a service facility for heterogeneous drones used in different services. Droneport is designed to charge, maintain and manage drones coming in and coming out. Diverging from a recent trend, the design of droneport focuses more on air traffic control and regulation enforcement.

Based on the idea of droneport, an optimization method is developed. The future drone demand for e-commerce purpose was predicted using the Holt-winters seasonal method, then we developed an optimization model for droneport placement. By assessing both fitness value and six objectives, the optimum number of droneport can be chosen. In the proposed model, we used e-commerce demand coverage, passenger delivery demand, drone flight distance, subzone coverage and area coverage as optimization criteria. Demand coverage, drone flight distance, and subzone coverage are related to point to point mission, while area coverage is associated with area-based mission. These two types of mission represent almost all applications of drones. With considering uncertainties in real life, Gaussian noise was integrated into drone flight distance calculation, making the model more realistic and practical.

Results presented in the paper can be used in the future development of the drone system. As a complement to this study, future studies will look into droneport infrastructure design based on droneport capacities and air traffic control implementation. The former consists of instruments, ‘taxiway’, take-off and landing pads, and safety-controlled area; the latter includes obstruction analysis, drone separation analysis, urban airspace classification, approach procedure design for droneport and emergency procedure.

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TABLE II  
OPTIMUM SOLUTIONS FOR 6-9 NUMBER OF DRONEPORTS.

Number of Droneports (N)	Fitness values	Parcel demand coverage	Passenger demand coverage	Parcel service distance (10 <sup>7</sup> km)	Passenger service distance (10 <sup>7</sup> km)	Subzone coverage	Area coverage
6	2.91	95.5%	100%	1.15	75.4	86.1%	88.3%
7	3.18	99.0%	100%	1.21	92.2	89.5%	91.3%
8	3.47	99.9%	100%	1.33	97.2	90.7%	91.4%
9	3.77	99.9%	100%	1.49	109.0	92.0%	91.8%

TABLE III  
OPTIMUM LOCATIONS AND ANNUAL CAPACITY FOR 7 DRONEPORTS.

Droneport	Coordinates	Annual capacity in 2022 (million orders)
1	(1.428941, 103.815767)	37.4
2	(1.331394, 103.732642)	38.8
3	(1.306954, 103.818726)	35.8
4	(1.333459, 103.875616)	56.5
5	(1.369987, 103.756191)	40.7
6	(1.346860, 103.937523)	44.2
7	(1.381924, 103.879566)	62.9

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