Droneport Placement Optimization and Capacity Prediction

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***Abstract*—Increasing demand for Unmanned Aerial Vehicles (UAVs, or drones) in urban airspace brings many concerns about safety issues. Take-off, approach and landing phases of drones have a strong occurrence possibility of accidents and incidents. Concerning the potential safety issues of thousands of drones taking off and landing in the metropolitan areas, we conceive a facility called droneport to accommodate and manage assorted drones in a protected space, which is suitable for applying air traffic control to departing and approaching drones. This paper presents several contributions to the concept of droneport: (1) The Holt-Winters' seasonal method was adopted to forecast future delivery drone demand based on historical online retailer data. (2) A multi-objective optimization model was established to determine the optimum placement and number of droneports considering both costs and societal value from three aspects: maximizing e-commerce demand coverage, minimizing drone service distance and maximizing area coverage. (3) Gaussian noise was introduced to the optimization model to make the measurement of service distance more practical. (4) The future capacity of each droneport was estimated. A real-world case study was carried out for Singapore. Developed on the forecasted demand distribution, the optimization result with 7 droneports and a 10 km radius of operation showed a 99% demand coverage and 93% subzone coverage. 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.**

Keywords-UAV, drone, Air Traffic Control, droneport, drone demand, optimization

I. INTRODUCTION

Many civilian applications of Unmanned Aerial Vehicles (UAVs, commonly called drones) have been recently proposed, such as goods and passenger delivery, surveillance, search and rescue, sports events and agricultural monitoring, etc. The e-commerce sector has been attracted by this trend, and companies such as Amazon [1], Google [2], Uber [3] and DHL [4] have developed various projects on drone delivery. The investigation is on the feasibility of drone delivery by looking at its economic viability and potential benefit to society [5, 6] and shows that drone delivery has high potential to be implemented in the future. However, as the drone delivery market grows rapidly, it will cause a proliferation of drones in the airspace. Especially in the highly populated urban areas, it presents a serious hazard for other vehicles, people, industrial facilities, and the environment [7]. Safety thus becomes a critical issue that must be addressed and regulated.

In a statistical analysis report done by Airbus [8], most of the commercial aviation accidents from a 20-year period (1999-2018) happened during the approach and landing phases. Just like commercial aviation, Remotely Piloted Aircraft System (RPAS), a subcategory of the unmanned aircraft system (UAS) equipped with remote pilot stations and command and control stations [9], also has a similar distribution of accidents regarding different flight phases. Wild et al. [10] analyzed the data of accidents and incidents from 152 RPAS events over 10 years (2006-2015). The study shows that take-off, landing and approach phases account for a large proportion of RPAS accidents and incidents. Small RPAS used in civilian aviation is usually called drone as well. It is significant to ensure that drone operations to be safe for the general public. Given a high occurrence possibility of accidents during take-off, approach and landing 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 [11], which describes a multi-level fulfillment center for UAVs. However, droneport is proposed to accommodate heterogeneous UAVs including not only 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, and reliable technologies as well as regulations including air traffic flow management are its fundamentals 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) [12], 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 taxi. The combination of trucks and drones for cargo delivery is called last mile delivery [13], and the passenger delivery by taxi and drone has been well studied by Uber Elevate [3]. Some operational concepts and technologies involved in the design of droneport have been investigated in Metropolis project [14].

To established urban areas such as Singapore, the questions raised are about where to distribute these droneports in an optimal manner with respect to potential demands 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 [15]. Using this predicted number of online orders, we estimated the future demand of drones, as the forthcoming drone market will be mainly driven by delivery use. Then we used UAV's constraints to define the radius of operations and established an optimization model that consists of three objectives, which are (1) maximize e-commerce demand coverage, (2) minimize drone service distance with Gaussian noise and (3) maximize area coverage. This model aims to optimize droneports locations and thus determine an optimum number of droneports.

A substantial number of works have emerged for optimizing drone fulfillment center locations with stochastic demand and the objective of minimizing the total costs. The optimization model presented in this paper uses forecasted drone demand and considers not only costs but also societal value.

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

Different from traditional logistic transportation, commercial UAVs currently cannot achieve long-term missions without frequent set-up of recharging stations or refueling depots. Many early studies thus focus on system scheduling and path planning with pre-determined service stations in disparate geographic locations. Song et al. [16] dealt with path planning for single UAV and multiple refueling depots. Song et al. [17-19] and Kim et al. [20] adopted battery recharging stations as logistics facilities and modeled the problem with UAV mission scheduling and guidance system using mixed-integer linear programming (MILP). In [21], the authors developed solutions for mission planning for a various number of charging stations with consideration of uncertainty and dynamic environments.

As UAV delivery becoming one of the emerging areas of UAV utilization, there is a rise of studies on UAV delivery logistics and many works have started to incorporate more factors into the modeling of the problem. One of those factors is loading capacity because battery capacity or flight duration is not the only limitation of commercial UAVs. Song et al. [22] made efforts on an improved MILP model and a persistent UAV cargo delivery operation considering both loading capacity and flight duration limitations of UAVs. In their work, the battery recharging stations are designed not only to refuel but also reload packages. In 2017, Amazon [11] brought forward a multi-level fulfillment center for UAVs to deliver parcels. This patent's viability was checked by Aurambout et al. [13] via investigating its economic potential in European urban areas and allocating the fulfillment centers through optimization. They emphasized that the setup of such fulfillment centers needs regulatory measures regarding drone flights and policy implications in the form of safety, air traffic, and environmental nuisance. Other than that, Uber [3] has proposed the passenger delivery drones landing and taking off from vertiport and vertistop, which would be allocated on the floating barge, highway cloverleaf, and top level of parking garages, etc. Uber also modeled the drone demand, routes, and costs for passenger transportation using existing infrastructure. However, this paper only focuses on cargo delivery drones.

Akin to hub location problems [23], the optimized location of drone service stations like recharging stations or fulfillment centers is of great interest to reduce the constructional cost and operational cost. Following this objective, some of the existing articles aim at finding the optimum locations for recharging stations. For instance, [24] and [25] developed models to locate the recharging stations which maximize demand coverage while minimizing the average flight distance between warehouses and recharging stations. These models were integrated with Euclidean Shortest Path (ESP) problem, which dealt with polygonal obstacle avoidance. Other studies focused on optimizing locations for both recharging stations and warehouses. Shavarani et al. [26] found the optimum number and locations of recharging stations and warehouses in San Francisco through evaluating the total cost of delivery logistics. In their work, the demand is assumed to be set on the edges of the network, and it is estimated based on Poisson distribution. Inspired by Amazon's fulfillment centers, a recent study [13] formulated the logistic location problem to position the fulfillment centers, which combines recharging stations and warehouses.

Apart from allocating delivery facilities, some researchers examined the optimum distribution of center locations for disaster relief operations. In [27], the last-mile distribution in the humanitarian logistics problem was formulated to locate recharging stations, and the objective of the optimization model was to minimize the total flight distance, flight time and costs. Chowdhury et al. [28] also worked with last-mile distribution problem, but they considered different optimization targets, including the location of integrated facilities and emergency supply centers.

Most articles aim at minimizing the total costs of drone operations, such as cargo delivery [13, 24-26], passenger delivery [29] or disaster relief [27, 28]. It is no surprise that the logistic location problem for drone delivery emphasizes operational economic viability. However, in many operations such as disaster relief, 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 objective therefore not only focuses on minimizing cost, but also maximizing demand coverage and geographic accessibility. 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 the environment such as wind and physical obstacles and their flight path may change from designed route instantly. The next section presents the details on the problem formulation based on the following: i) total demand coverage, ii) total dynamic flight distance and iii) area coverage.

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. In this section, an optimization problem is formulated. 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-determined droneport number, and the second is to obtain the optimum droneport number via comparing the value of three energy terms listed below.

The following sections start with multiple energy terms that constitute the objective function, after which the final optimization algorithm is introduced.

A. Energy Terms

Let the number of droneports be *N*. The coverage of droneport is constrained by the delivery drone's maximum travel range. As proposed in Amazon's Prime Air project in 2013, a delivery drone is going to have an endurance of 32 km and 30-minute travel time [30]. In 2019, this data was updated to be 24 km and less than 30 minutes respectively with a payload under 2.3kg [31]. 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 [32], in which 10 km is defined as a high-range drone carrying a 2.3 kg parcel.

The objective function consists of three energy terms: demand coverage, service distance and subzone coverage.

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

$$Q = \sum_i^N \sum_j^M \left\lceil 1 - \frac{d_{ij}^2}{r^2} \right\rceil_+ * q_j, \qquad (1)$$

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. $\lceil 1 - d_{ij}^2/r^2 \rceil_+$ 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, which is defined as

$$d_{ij} = \left\| (x_i, y_i) - (x_j, y_j) \right\|_2, \qquad (2)$$

where x and y are the Universal Transverse Mercator (UTM) coordinates of droneports and subzones in meters.

Intuitively, maximizing this term tends to cover more demand in an urban area with a limited number of droneports. Finding a minimum number of droneport to cover maximum demand can reduce land-take and save costs of establishments.

Service distance. Given an area and a droneport, one optimization criterion to decide the droneport location is to minimize the total service distance between this droneport and its subzones. 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.

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

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

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

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

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

The variance σ_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 σ_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 ${h_{ij}}^2/r^2$ 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.

Since drone travel distance is proportional to its energy consumption, minimizing the cumulated drone service distance will help to reduce drone charging time and reduce drone usage costs.

Subzone coverage. The last factor considered in the objective function is area coverage. To measure the percentage of subzones covered by all droneports, we use the mask term $\left[\sum_i^N \left[1 - d_{ij}^2/r^2\right]_+ / N\right]_+$ to tally the covered subzones.

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

When optimizing a droneport location for assorted applications such as search and rescue, disaster relief, and surveillance, area coverage should be considered as one of the most important factors. Diverging from previous energy terms, this term targets to maximize the geographic accessibility of drones to achieve utilization of drones for different services. For example, to recognize, respond, assess and relieve the unknown disaster quickly and efficiently, a fully recharged drone and an accessible distance between disaster area and drone launch station, as called droneport in this paper, are necessary.

B. Optimization Model

In this optimization model, four missions are mainly considered: (1) cargo delivery, (2) disaster relief, (3) search and rescue, and (4) surveillance. Drones are capable to fly from a droneport to other droneport or from a droneport to a subzone then to any droneport in its flight range.

With the above energy terms, the optimal locations of droneports can be obtained by maximizing a weighted sum of these terms as defined below,

$$f(X, Y) = \sigma * Q - \delta * D + \eta * S \qquad (7)$$
$$x_i \in X, y_i \in Y .$$

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. Under these conditions, the final formulation for this optimization can be written as

Maximize $\quad f(X, Y)$

Subject to

1) $d_{ip} > r, i = 1, \cdots, N, p = 1, \cdots, N$

2) droneport network connectivity

where d_{ip} is the Euclidean distance between droneport i and droneport p.

$$d_{ip} = \left\|(x_i, y_i) - \left(x_p, y_p\right)\right\|_2 \qquad (8)$$

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 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 [33], Shopee annual report [34] and Amazon [35]. No survey and study show the e-commerce demand distribution in Singapore, and thus the population distribution [36] is used as a reference. We assume that these two types of data are following the same distribution.

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 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. 2*.

There are two forecast methods, with additive and multiplicative seasonality respectively, applied in the Holt-Winters method. The former is appropriate for a time series with roughly constant seasonal variations, while the latter is more suitable for a time series with seasonal variations proportional to the level of the series. However, due to the limited scale of the obtained data, we cannot conclude which method is more appropriate in this case. Although the data is insufficient, the trend and seasonality of AOV are obvious. The slowly descending of predicted AOV visible in *Fig. 2* 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 e-

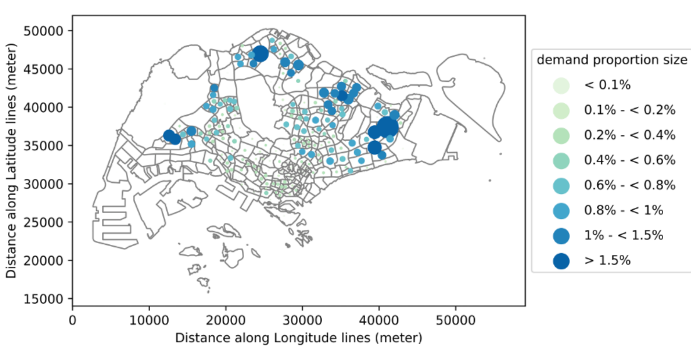

Figure 1. Demand distribution in Singapore in 2019 (150 million orders ≈ 0.4 million orders per day).

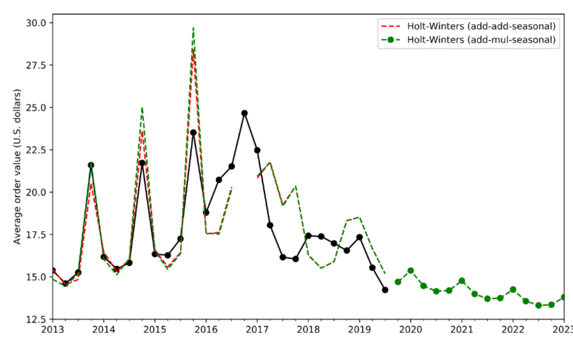

Figure 2. Average order value (AVO) forecast from Holt-winters seasonal method.

Table 1. 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

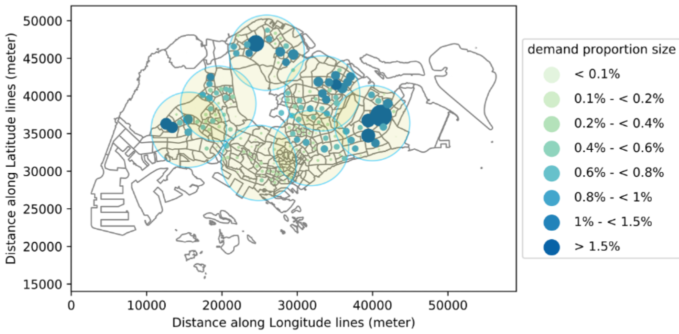

Figure 4. Spatial distribution of 7 droneports in Singapore resulting from the optimization model

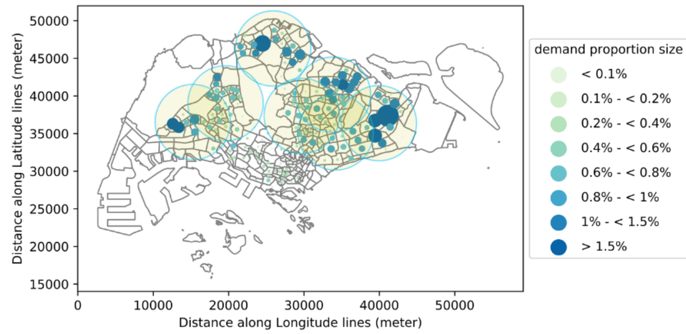

Figure 3. Spatial distribution of 7 droneports in Singapore resulting from the baseline model.

Table 2. Optimum solutions for 6-9 number of droneports.

Number of Droneports (N)	Fitness values	Demand coverage	Service distance (km)	Subzone coverage
6	1.6661	94.1%	7.60×10^8	84.5%
7	1.8077	99.0%	7.68×10^8	91.6%
8	1.9003	98.8%	8.18×10^8	92.6%
9	1.9819	99.7%	9.40×10^8	93.2%

commerce revenue customer behavior of these two companies. Combing annual AOV and total in Singapore [33], we can predict the number of orders from 2020 to 2022 (*Table 1*).

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.

B. Optimization Results

The optimization algorithm proposed in section 3 was implemented in Python 3 and the solver was constructed using the Platypus library [37]. 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 σ and δ gains significance to achieve this balance. Paired T-test was conducted to compare the performance of six sets of weight parameters, and the combination of 1, 1.25, and 1.3 for weight parameters σ, δ, and η respectively surpasses among all sets in demand coverage and subzone coverage. However, the T-test results reveals no much difference among all sets on the service distance.

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 2*. We then compared the optimization performance of different N and concluded that 7 is the optimum number of droneports, because the result of 7 droneports provides a comparable subzone coverage value and demand coverage and also shows the shortest service distance among 4 results. *Fig. 3* illustrates the spatial distribution of 7 droneports in Singapore.

We also compared the performance of the optimization model developed in this paper with a baseline model, which only considers minimizing service distance and maximizing demand coverage as objectives. This baseline model was constructed according to cost-oriented models shown in works of literature, and all weight parameters were set to 1. The result of 7 droneports subsequentially collected from baseline (*Table 3*). It shows +10.4%, -13.3% and +28.4% improvement over baseline model on three objectives, demand coverage, total service distance, and subzone coverage, respectively. The spatial distribution of 7 droneports generated by the baseline model is depicted in *Fig. 4*.

Based on the optimized result, the annual capacity of each droneport, also the potential demand in each area defined by the range that each droneport could attend, are shown in *Table 4*.

Table 4. Comparison between baseline model and our optimum solution

7 droneports	Demand coverage	Service distance (km)	Subzone coverage
Baseline	88.6%	8.86×10^8	63.2%
Optimum solution	99.0%	7.68×10^8	91.6%

Table 3. Optimum locations and annual capacity for 7 droneports.

Droneport	Coordinates	Annual capacity in 2022 (million orders)
1	(1.338789, 103.720211)	30.9
2	(1.316791, 103.866021)	37.5
3	(1.298919, 103.803737)	29.5
4	(1.382466, 103.879376)	63.9
5	(1.346696, 103.938985)	44.0
6	(1.431388, 103.813283)	37.3
7	(1.370185, 103.755468)	40.3

The optimum number of droneport does not guarantee a 100% demand coverage and subzone coverage, because it is not worthy to cover those areas with zero population density. Thus, small charging stations are still necessary. However, we aim to optimize the placement of droneports and obtained their capacities, and small charging stations are excluded in our study.

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. CONCLUSION

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 three energy terms, the optimum number of droneport can be chosen. In the proposed model, we used e-commerce demand coverage, drone flight distance, and area coverage as optimization criteria. Demand coverage and drone flight distance are related to economic viability, while subzone coverage is associated with social/humanitarian benefit. With considering uncertainties in real life, Gaussian noise was integrated into drone flight distance calculation, making the model more realistic and practical. Comparing to the baseline model, we show that our optimization model performs effectively and efficiently and has a huge improvement.

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 capacity and air traffic control implementation. The former consists of instruments, 'taxiway', take-off and landing pad and safety-controlled area, and the latter includes obstruction analysis, drone separation analysis, urban airspace classification, approach procedure design for droneport and emergency procedure.

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