# A Two-Layered Task Servicing Model for Drone Services: Overview and Preliminary Results

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***Abstract*—We envision a future with companies providing civilian drone services to people - e.g., photo-taking on-demand for tourists from impossible (such as from off-the cliff) perspectives, object inspection, delivery, guarding, or helping someone check something out remotely. The broad aim of our work is to provide a framework for the cooperation between one or more stations and one or more drones as they are allocated to tasks. This paper has two contributions: (1) we propose a two-layered task servicing a model that couples the "big picture" across-drones perspective of drone stations, and the dynamic local perspective of drones, in order to decide which task a drone should serve next, where tasks are first allocated to a drone's task set via an on-station strategy, and then drones select tasks to serve from their respective task sets via an on-drone decision-making strategy, and (2) we report on our preliminary results on simulations to assess the impact of different station strategies (i.e., round-robin vs. serve-near), a selected drone strategy (i.e., utility function based), for different kinds of client distributions (i.e., random, scatter-near, scatter-middle, and scatter-far), and for different numbers of drones. Our results show that the round-robin system performs better in most situations than serve-near for the allocation strategy.**

***Index Terms*—drone, UAV, drone services, on-station decision-making, on-drone decision-making**

## I. Introduction

Unmanned Aerial Vehicle (UAV), or also known as drones, are likely to become an important type of vehicle in the developed urban environment of the future. There are various studies that use different methods to increase use of drones in a smart city [1] by introducing new properties that allow drones to be more self-aware [2], [3], [4]. Drones can be used in the context of service delivery where they undertake different types of tasks at varied locations. We argue that in order to deliver a service, the decision process requires two main components: On-Station allocation of tasks/requests to drones (or how tasks are added to the workload, or task set, of each drone) and On-Drone decision-making (to decide which tasks/requests to next handle within a drone's workload). There are various aspects involved in each component, some of these aspects are crucial to the component itself and others can be shared amongst both. For example, drones could experience anomalies during flight, such as, inner failure, changes in the environment, or communication issues so that decisions need to be quickly made on the drone itself while in-flight [2].

In a previous study [5], we showed that the stations location could play a key role in processing orders. Also, the number of stations and the number of drones at each station may significantly affect the process of making decisions. There are four scenarios to be considered: *Single Station - Single Drone, Single Station - Multiple Drones, Multiple Stations - Single Drone,* and *Multiple Stations - Multiple Drones*. Other factors that may affect the decision in the context of drone service delivery are discussed in Section III-D.

We investigate possible strategies for a station to allocate received tasks/requests to its collection of drones, given each drone also has its own decision-making module (to select the next task/request it will serve from its allocated set), and to identify some common factors that may affect the decision-making processes when deploying drones to serve people. We present preliminary results on how different on-station drone strategies work, where the drones and the stations have their own strategies, but are coupled together within the one framework.

## II. A Task Servicing Model for Station and Drone Strategy Coupling

### A. Overview

The decision-making model consists of two main layers as shown in Figure 1, these are the stations and drones. Each component consists of a set of instructions (On-Station & On-Drone) taking aspects such as the number of stations and the number of drones into account.

### B. Station Centre (SC)

The SC is responsible for receiving requests that come from clients. These requests can be handled in various ways. Depending on the factors that may affect the decision process, SC has two states; Idle, where SC waits for upcoming requests, and Processing, where SC makes the decision either to send the order to an individual station instance or an individual drone.

### C. Drone

A drone has four main states; AtStation, OnRouteToClient, ServingClient, and OnRouteToStation. It can receive instructions in any state and then it has to decide which request to serve, upon receiving the request from the SC or an individual station.

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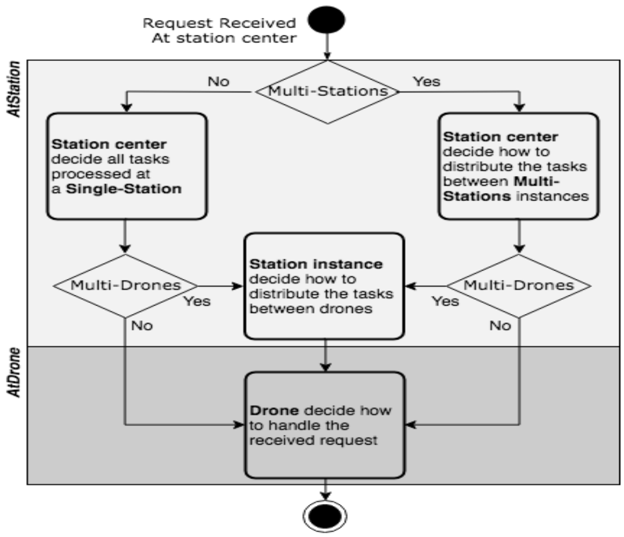
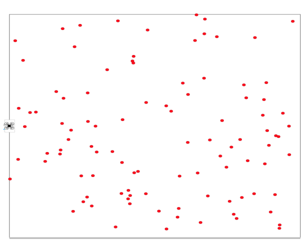


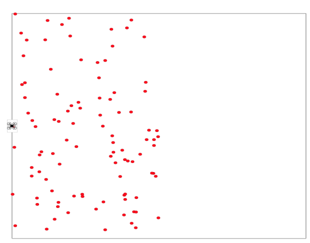

Fig. 1: Two-Layered decision model for task servicing by drones.

*D. Simulated Study Area*

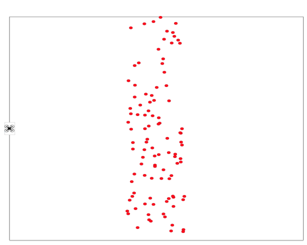
In order to provide a better understanding of the decision-making model. We have assumed the study area to be a square with a side length of $L$. Stations can be located at the edge or anywhere within the area [5]. Clients can be located in the area using different distributions such as random, scatter-near, scatter-middle, and scatter-far as shown in Figure 2, with station marked “x”.



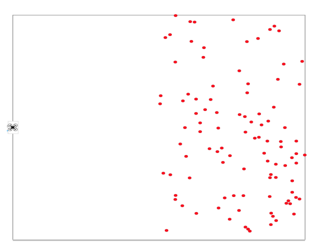
(a) Random



(b) Scatter-Near



(c) Scatter-Middle



(d) Scatter-Far

Fig. 2: Clients’ distributions

## III. Experimentation

*A. Overview*

The process of determining which task a drone should serve next involves considering a range of factors, constraints, and the objective function. The objective of the task servicing can vary from seeking a particular value, minimisation or maximisation. This section presents the common factors involved in the decision-making process followed by two objective functions. It then presents our simulated approach for coupling the decision-making process of the stations with drones using the AnyLogic[1] simulation tool. Our study simulates drones servicing clients with requests/tasks for a one hour period - we study the system behaviour focusing on the number of served requests, total revenue generated and the total time that a client has to wait to be served, from issuing the request until the drone’s arrival.

*B. Objectives*

There are lots of objectives that are possible for drone service providers. For the purposes of this experiment, we have set the following two objectives: (1) maximise profit, and (2) minimise the travel distance. It is likely that these objectives will be included in almost all commercial drone service deliveries.

*C. Implementation*

We study different strategies for the station centre allocating requests to drones to enhance drone services delivery. In the study area with (L = 1000 m), the station is located at the edge and clients are located using four different distributions as discussed earlier. The steps in running the simulation are: 500 clients periodically send requests to the SC at an average rate of $\alpha = 1$ request per hour. Once a request is received, the SC needs to decide which drone need to service the request. It then forwards the request to the shortlisted drone. A number of drones (i.e., 2, 4, 6, 8, 10) were used, where each has a speed of 10 m/s, a processing time of $v$ seconds and a battery life of one hour. Once a drone receives the request, it has first to decide whether it should queue the job (based on the acquired strategy) or proceed to the client if there is no orders in the queue. If a drone battery is insufficient, SC will not assign more requests to it. As the simulated time period is for an hour, in this study, we assumed that all drones are capable of handling the assigned tasks.

*1) SC strategies:* In this experiment, we only consider the case of Single station - Multiple drones scenario. The individual station can then assign a task to a drone based on:

- A round robin system where tasks are distributed cyclically to the available drones, in turn.
- Proximity to the client requesting the task to be done, where the nearest drone to the client will be in assigned to the task.

*2) Drone strategies:* In this experiment, we only consider two factors to build the drones strategies for handling the upcoming requests: distance-based and value-based (financial incentive). Each order request has a value ($v$) and a determined distance ($d$). Since there are multiple attributes, for the sake of

[1]https://www.anylogic.com

simplicity, we have described the variables and the parameters to run the experiment below.

**Distance Scale ($dS$):** As mentioned earlier, the study area (i.e., a square) has a known length of $L$, so the maximum distance ($d_{max}$) that a drone can travel to is the diagonal of the area ($L\sqrt{2}$). So to scale each order based on the proximity of the drone, we calculate it as shown in (1):

$$dS(r) = \frac{d(r)}{d_{max}} \tag{1}$$

where $d(r)$ represents the distance between the drone at its current location when $dS$ is computed, and the client with request $r$.

**Value Scale ($vS$)**: Each order has a value ranging from $v_{min}$ to $v_{max}$. We divide the value of the request $r$ ($v(r)$) by $v_{max}$ to standardise the value of the current job as in (2), where $v$ represents the value of the order that has been received:

$$vS(r) = \frac{v(r)}{v_{max}} \tag{2}$$

Note that in our simulation, time spent by a drone at the client's location for a request $r$ depends on its $v(r)$.

**Preference weights ($w$)**: Preferences or priorities values for both distance ($w_d$) and value ($w_v$) are weighted equally in our simulation study here (though other weights can be experimented with), where:

$$w_d + w_v = 1 \tag{3}$$

**Utility function ($U$)**: We need to consider the scale values and preference values in computing the utility for each request that has been received ($r$).

$$U(r) = w_d \cdot dS(r) \ + \ w_v \cdot vS(r) \tag{4}$$

**Processing**:There are 5 scenarios to be considered in drone orders processing:

1) Request received while the drone is at the station - drone will go to the client
2) Request received while the drone is serving another order - drone will add the order to its requests list.
3) Request received while the drone is going back to the station - drone will go to the client.
4) Request received while the drone is on route to a client. In this case, drone uses the utility function to compute the request with the highest utility *U*.
5) The drone finished the current request but still the requests list is not empty - the drone will pick up the next order of highest utility.

### D. Common Factors

The most common factors in decision-making in the context of drone services delivery (for SC and/or drone) are:

- **Power and battery life**: Drones or stations need to consider the available level of power (i.e., battery life left, consumption rate and charging rate if applicable) in the context of the service. If the drone does not have sufficient power to carry out the task then it would make sense for the drone not to undertake that task. If a drone accepts a task which it is not able to carry out fully, then this could be counterproductive.
- **Distance**: The distance between the client and the station, the distance between the client and the current drones location, and the distance between the current drones locations and the station are essential factors in making decisions about drone service delivery.
- **Financial incentive**: The amount of value or financial incentive associated with a particular service request can determine the amount of resources allocated to a job in the context of commercial jobs. For example, the decision-making process can be driven by different rules in cases of high value service requests.
- **Range**: The range in this context is not defined as the distance that the drone is able to cover with the available battery life, but maximum distance that the drone needs to be away from its controller before it loses connectivity with its controller. Whilst there is a lot of drones which no longer need to be in the proximity of the controller, there are still drones which needs to be within range of their controllers [6]. In our simulated study, we assumed that all drones are within the communication range of their station.
- **Environmental factors**: Environmental factors can be natural factors like temperature, pressure, visibility, and humidity; or factors like no-fly zones. The drone can receive environmental factors through sensors it might have or through data feeds from external sources. It is important for the drone to consider the environmental factors for a number of reasons, some of these are: to prevent damage to itself, to ensure the quality of the task that the drone has been assigned, and to ensure the legality of the operation. In this study, we assumed that drones operate with no environmental restrictions.

### E. Results and discussion

The simulations were run with Anylogic software for various combinations of station and drone strategies, and for different numbers of drones. As mentioned previously, the station has two strategies it can follow, i.e., round-robin (R-R) and serve-near (S-N). The drone can follow many strategies; we have chosen the utility value based strategy for the experimentation. Table 1 shows the results of the simulations for scenarios with 2, 4, 6, 8 and 10 drones; four types of client distributions of random, scatter-near, scatter-middle and scatter-far; and the numbers of served orders and total profits corresponding to the station strategies of R-R and S-N.

The results of the analysis in Table 1 indicates that on average, more orders are served and more profit is generated when the station assigns jobs based on R-R as opposed to S-N. The distribution of the client does not have much impact on the number of orders served and profit generated under R-R. However, under S-N, there is high variability in the orders served and profit generated by the client distribution. The number of orders served, and profit generated increased with

TABLE I: Results for different strategies

| #Drones | Distribution | # Served orders | | Total Profit | |
|---|---|---|---|---|---|
| | | S-N | R-R | S-N | R-R |
| 2 Drones | Random | 126 | 130 | 6820 | 6830 |
| | Scatter-Near | 128 | 126 | 6760 | 6940 |
| | Scatter-Middle | 109 | 127 | 6220 | 6960 |
| | Scatter-Far | 64 | 133 | 3510 | 6870 |
| 4 Drones | Random | 236 | 234 | 12670 | 13390 |
| | Scatter-Near | 215 | 241 | 12040 | 13690 |
| | Scatter-Middle | 152 | 245 | 8620 | 13640 |
| | Scatter-Far | 129 | 249 | 6630 | 13630 |
| 6 Drones | Random | 267 | 349 | 15640 | 19430 |
| | Scatter-Near | 232 | 357 | 13170 | 19820 |
| | Scatter-Middle | 207 | 353 | 11550 | 19870 |
| | Scatter-Far | 122 | 365 | 6850 | 19850 |
| 8 Drones | Random | 238 | 454 | 12840 | 24780 |
| | Scatter-Near | 265 | 463 | 14980 | 25100 |
| | Scatter -Middle | 188 | 461 | 9980 | 25100 |
| | Scatter-Far | 120 | 462 | 6660 | 25050 |
| 10 Drones | Random | 279 | 491 | 14680 | 26560 |
| | Scatter-Near | 280 | 492 | 15000 | 26580 |
| | Scatter-Middle | 117 | 491 | 5830 | 26560 |
| | Scatter-Far | 68 | 491 | 3500 | 26560 |

an increase in the number of drones for R-R, but this is not necessarily true for S-N, the reason being that, a drone can be overwhelmed with many orders just because of its current position.

Figure 3 shows the average clients' waiting time for each strategy and distribution. The clients' waiting time is an important measure of the quality of drone service as it is directly related to client satisfaction. Longer waiting times are often associated with relatively lower customer satisfaction [7]. Therefore, the client waiting time has been chosen to assess the merit of each strategy and distribution. Only the served orders were considered in the calculations of waiting times. The results of the analysis indicate that, in general, the minimum waiting time for all four distributions has been obtained for the 10-drone scenario when using R-R. Additionally, there is

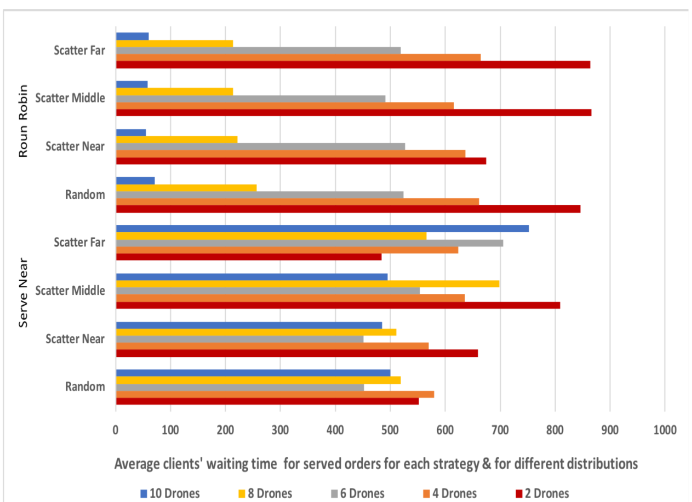



Fig. 3: Average client waiting time for served orders for each strategy.

a clear relationship between the number of drones and waiting time for R-R, where the waiting time increases as the number of drones decreases. For S-N, even with more drones, the waiting times tend not to decrease since S-N tends to use drones already deployed rather than drones at the station, so that S-N tends to under-utilise drones or not utilise all drones. Also, it can be seen that from 2 to 6 drones, S-N has lower average wait times compared to R-R, since deployed drones nearer to the clients are assigned the tasks, rather than idle drones from the station (in particular, the Scatter-Far scenario). But then, as the number of drones increased from 6 to 10, the increased number of drones then compensated for the travel from the station so that R-R decreases wait times significantly by better utilising all the drones - in particular with 8 or 10 drones. The above indicates that one can even adapt station strategies depending on the available drones.

## IV. Conclusion

This paper provides a framework for the cooperation between one or more stations and one or more drones. Simulations were run to assess the impact of the various combinations of station strategies and a selected drone strategy, different client distributions, and different numbers of drones, on the number of orders served, profit generated and customer average waiting times. The results have found that for all kinds of client distributions more orders can be served and profit generated if the station centre follows the round robin strategy for job allocation as opposed to the serve near system, when there are enough drones. The round robin system was also found to be distribution agnostic which is better in practical scenarios as the clients could follow any distribution. Also, using a higher number of drones was also found to be associated with more orders served, more profit generated and minimal waiting times for the clients. Future work will explore other on-station strategies, and on-drone strategies and how that inter-plays with station strategies, and consider other urban drone service settings.

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