On-Drone Decision Making For Service Delivery: Concept And Simulation

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***Abstract*—We imagine drone service providers where one can phone-a-drone to provide a service (e.g., rent a drone to check out something, or for two minutes to take an interesting photo). There are different types of drone services that can be implemented in different scenarios. For example, a drone can act as a security guard to protect someone walking home alone at night or a drone can act as a flying camera that can be rented simply by calling the drone to come to a given location to take photos or videos. This paper aims to study the trade-off between maximising provider revenue and maximising clients satisfaction in the context of drone services, which we argue do not necessarily concur. We have considered possible drone strategies and identified common factors that may affect the decision-making process. The research has implications for service providers - e.g., a service provider should aim to address high rates of requests but not at the cost of disappointing clients.**

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

I. Introduction

Unmanned Aerial Vehicle (UAV) or drones are on the edge of delivering a superior level of services. The metropolis project is developing a program to study the influence of airspace structure on different functions for accommodating more drones [1]. Other projects are developing Air Traffic Management (ATM) systems such as SESAR and NextGen [2]. This is indicative of the fact that there are ongoing developments and modern infrastructures that are preparing for the future of smart environments with drones.

On the drone side, work is being done on introducing new properties that allow drones to be more self-aware and autonomous [3], [4], [5]. In parallel, drones can be used to conduct different types of tasks at wide-ranging locations. The decision making in drones need to be designed in such a way as to allow drones to make decisions on the go.

This requires, first of all identifying all the factors that go into the decision-making, managing all the constraints, the objectives, and a hierarchical framework to deal with competing objectives. Whilst the optimisation of drones decision making is fairly well evolved [6], the optimisation of drones decision making in the context of service delivery is not.

There are various aspects involved in the decision making process. For example, drones could experience anomalies during flight, such as, inner failure, changes in the environment, or communication issues [3]. In dealing with such situations, decisions should be made real-time on the drone itself while in flight, rather than from the station end.

In a previous study [7], we showed that a drone can process tasks requiring no knowledge or intelligence as its been fully controlled by the station centre. However, drones can be fully or partially autonomous to perform tasks that are difficult for a human pilot to perform.

In the context of drone service delivery, this paper investigates possible trade-offs between maximising revenue and maximising clients satisfaction by exploring possible drone strategies and identifying some common factors that may affect the decision-making process. We also present some results on how on-drone decision-making could affect the profit gained and clients satisfaction.

II. The concept of on-drone decision making

A. Overview

The on-drone decision-making model presented here is to explore different strategies and to address the impact of various factors on the performance of drone services. Considering that a drone receives orders directly from clients or indirectly through a proxy (i.e., its station centre). Either way, once the instructions are received, then the drone needs to act upon the requests.

B. Drone

In our simulation, a drone act as a single independent agent that is connected directly to the station-centre and indirectly to clients. It has four main states: AtStation, OnRouteToClient, ServingClient, and OnRouteToStation as shown in Figure 1. Requests or instructions can be received by the drone at any state. However, the drone has to then decide whether it can take up a job upon receiving the request from the station-centre or an individual station.

C. Client

In our simulation, we assumed that clients have a direct connection to the station-centre. The behaviour of each client is modelled by two states: Idle, where a client is not issuing a request, and Requesting, where client issues a request based on a predefined rate as shown in Figure 2.

Also, we have assumed the simulated service area where clients are distributed to be a square with a side length of L.

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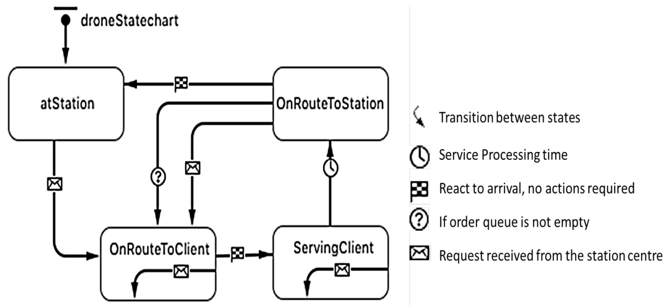


Fig. 1: Drone states.

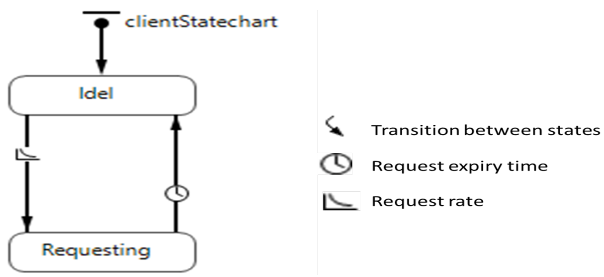
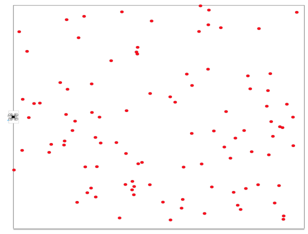
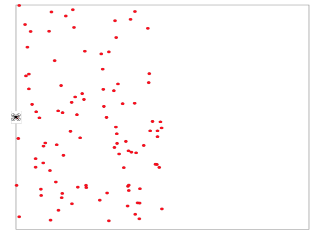


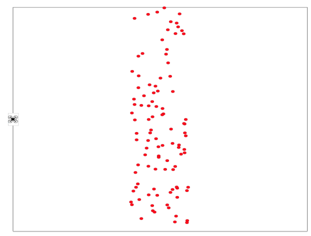
Fig. 2: Client states.



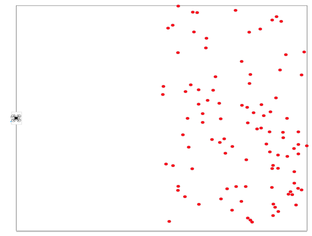
(a) Random



(b) Scatter-Near



(c) Scatter-Middle



(d) Scatter-Far

Fig. 3: Clients' distributions

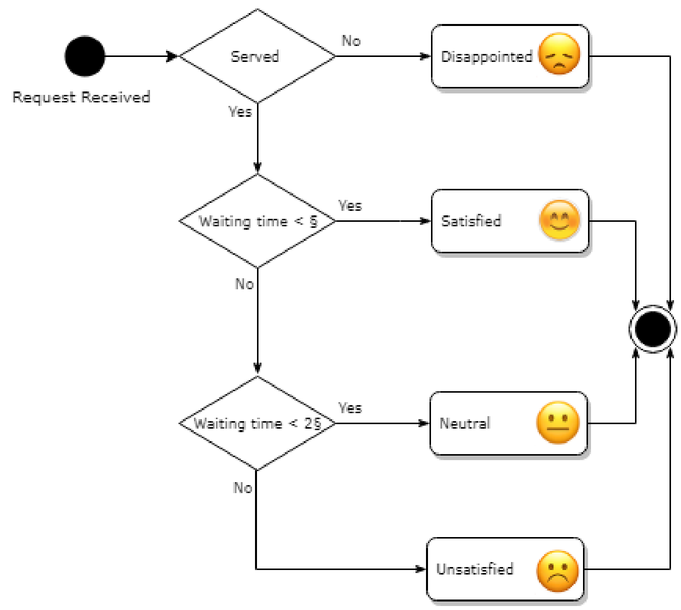


Fig. 4: Relationship between waiting time and satisfaction level of the client

Stations can be located at the edge or anywhere within the area [7]. Clients can be located in the area using different distributions such as random, scatter-near, scatter-middle, and scatter-far as shown in Figure 3, with station marked "x".

Client satisfaction is a key measuring variable for service provisioning. Longer waiting times are often associated with relatively lower customer satisfaction. Figure 4 shows the various scenarios and the associated client satisfaction levels. The client satisfaction levels can range from disappointed to neutral to satisfied, and depending upon the status of the delivery and waiting time. No delivery and a long waiting time are associated with dissatisfaction and delivery with a short waiting time are associated with satisfaction. Clients are satisfied if the waiting time is less than the satisfaction rate δ and neutral if the waiting time is less than double the time of δ. Other formulations of satisfaction can be explored but we explore this formulation in this study.

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 can vary from seeking a particular value, e.g., minimisation of waiting times, or maximisation of profits. This section presents various factors involved in the decision-making process following objective functions. It then presents our simulation for on-drone decision making using the AnyLogic[1] simulation tool. Our study simulates drones servicing clients with requests/-tasks in simulated time corresponding to a (real-world) one hour period (so that the effects of battery life is temporarily suppressed, for simplicity here, assuming one hour battery life is not inconceivable for future drones) - we study the system behaviour focusing on the number of served requests, total revenue generated, measuring clients satisfaction, and the time that the drone spends in each state.

B. Factors in choice of request to serve

Factors in decision-making in the context of drone services delivery (for SC and/or drone) include:

- **Power and battery life**: Drones or stations need to consider the available level of power (i.e., battery life

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

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, e.g. while on the way to a client, a drone can decide to change its mind to go after a higher value request.
- **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 [8]. In our simulated study, we assumed that all drones are within the communication range of their station.
- **Data storage and processing capacity**: Another important factor in the drones decision making is the amount of data storage and processing capacity that is required from a particular task. Tasks which require more storage space and processing capacity have to be matched against the amount of storage that is available in the drone and its processing capacity. If the hardware of the drone is not capable of undertaking the task to the full extent, then as described previously, it can be counterproductive to even initiate the task. This can be significant when providing drone data services.
- **Environmental factors**: Environmental factors can be natural factors like temperature, pressure, visibility, and humidity; or factors like no-fly zones. The drone can detect environmental conditions 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.

C. *Objectives*

There are lot of objectives that are possible for the drone service providers. For the purposes of the experiment, we have considered the following objectives:

- Maximising the number of served orders
- Maximising revenue
- Maximising clients satisfaction
- Minimising OnRouteToClient time

D. *Strategy Implementation*

We explore various on-drone strategies to enhance drone services delivery. We have specified a study area with ($L = 1000m$), station located at the edge and clients distributed using four different distributions as discussed earlier. The steps in running the simulation are: 100 clients periodically sends requests to the station at different average rates α (i.e 0.5, 0.7, 0.9) per hour. A drone has a speed of 10 m/s, a processing time of v and a battery life of one hour. Once the drone receives the request, it has to first decide whether it should queue the job (based on the acquired strategy) or proceed to the client if there are no orders on the queue. If a drone battery is insufficient, the drone will no longer receive a request. As the simulator time runs for an hour, in this study we assumed that a drone is capable of handling the received request within the one hour run time.

In this experiment, we study the effect of two main factors: distance (i.e. between the drone and the client) and value (financial incentive) in building the drones strategies for handling the upcoming requests. Each order has a value (v) (between 10 to 100) and a determined distance (d) between the current drone location and the requesting client. Each client is located at a position $\mho$ and the drone's current position is denoted as Ω. For the experiments, we have assumed that the satisfaction threshold is ($\delta = 100$) seconds. Each order/request (r) belongs to the order set $\mathbb{R}$, it is safe to say that $r \in \mathbb{R}$. Then we can calculate the the value $v(r)$ as the value of the requested order and the distance as $d(r) = \sqrt{(\mho_x - \Omega_x)^2 + (\mho_y - \Omega_y)^2}$.

1) Rules: As a drone can receive requests at any state, there are certain rules that need to be considered:

1) If the order is received while the drone is **at the station** - Drone will go to the client
2) If the order is received while the drone is **serving** another order - Drone will add the order to the orders list.
3) If the order is received while the drone is **going back to the station** - Drone will go to the client.
4) If the order is received while the drone **on route to a client** - *Decision required*
5) If the drone finished the current order but still the **order set is not empty** - *Decision required*

2) Scales, preference and Utility : In this context, scaling means allocating values to the received orders to determine the independent dimensions of different factors. The concept varies fundamentally depending on the chosen factor that can be measured. The focus here is on distance and value of each received order.

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 associate each factor with a specific variable based on a scale function. As the focus of these experiments is mainly on two factors, we used (1), (2) and (3) to formulate the utility function as shown in (4).

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

3) Strategies: We have conducted a set of experiments to assess the decision-making process, considering two factors; distance between the drone and the client and value of the request. Decisions are made to fulfil the purpose of rule 4 and 5 as discussed in Section III-D1. Five strategies are considered when deciding which order/request to serve next.

Distance-based($argmin$**)**: Clients with a closer proximity are preferred to be served first. Drone can find the nearest (location) of a client in the order list before committing to any request. An order with the shortest distance is always updated depending on the drone's location. Using this strategy will apply (5) for both rules.

$$argmin_{r \in \mathbb{R}}(d(r)) \tag{5}$$

Value-based($argmax$**)**: Orders with a higher value are preferred to be served first. Drone queue orders in a descending order based on their values. Choosing this strategy means that the drone always apply (6) when it performs a regular check (i.e on the order list) after each serve or as soon as it receives a new order.

$$argmax_{r \in \mathbb{R}}(v(r)) \tag{6}$$

Utility-based($U1$**)**: In this strategy, there are two cases to be considered. First, if an order (or request) is received while the drone is on the way to serving another order which we call the current order (r'), then the received order r will be compared only with r' in terms of distance and value using the scale values and preference value from (1), (2) and (3) respectively as shown in (4). Then, r is served first if $U(r) > U(r')$, otherwise r' is served. Second, if the drone finished serving the current order but the order list is still not empty, then let r' be assigned to the shortest distance order using (5), and let r be assigned to the highest value order using (6). The same applies again as in the first scenario, i.e. we compare $U(r' = argmin_{r \in \mathbb{R}}(d(r)))$ and $U(r = argmax_{r \in \mathbb{R}}(v(r)))$. Either of the scenarios above, the order with the highest U is served first for rule 4 and 5.

Utility based($U2$**)**: Each received order (r) is compared with each order/request in the order/request list. The comparison process has to consider each individual order against the order that has been received (r) using (4). The order with the highest U at the time r is received is served next, again for both situations in rule 4 and 5.

Utility-based($U3$**)**: This strategy is a combination of $U1$ and $U2$; it uses different action for each rule. If order received while the drone is flying to a client, the drone uses ($U1$) to fulfil rule 4. And as for rule 5 the drone uses ($U2$) to determine the next request to serve. The reason for this combination is that as the drone is flying to a client, this client already has the order with the highest utility value at the time (call this r') just before receiving r. Therefore, the drone does not compare r with all existing orders; it only compares (r) with (r') - this is a simple reduction in computations compared to $U2$.

E. Results and discussion

The simulations were run with Anylogic software for various combinations of drone strategies, and for different request rates δ. As mentioned previously, the drone can follow many strategies; only five strategies are tested here. The results of the experiments are shown in Figures (5 to 8) from the perspectives of orders served; total profit generated, client satisfaction and time spent in each state of the drone, respectively.

Figure 5 shows that, as expected, the maximum number of orders are served when the rate of requests is the maximum (i.e., 0.9), simply because there are more requests (and within the capacity of the drone). Also, with low-frequency requests, all strategies have similar outcomes. The utilities ($U2$ & $U3$) and the distance strategies are also highest under this scenarios compared to lower rates of requests. However, interestingly, the number of clients served using the value-based strategy remains relatively constant with an increase in the rate of requests and orders especially with the scattered distributions. This is most likely due to the drones being constrained by serving the high-value clients who might be a distance from the drone. If the high-value clients are widespread, then the drone will have to travel more distance to serve those clients, and that could result in serving the same number of clients using this strategy even for different rates of requests.

The results are similar on all fronts with varying client distribution except a slight negative change with the random distribution. The reason being that the scattered distributions are very similar but are a distance from the station. This possibility is more probable in this case, due to the size of

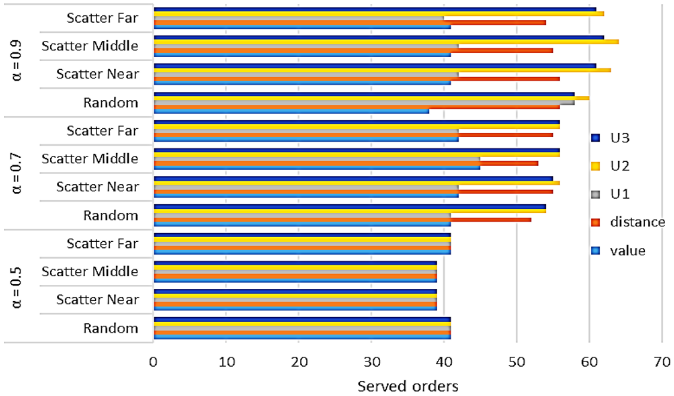


Fig. 5: Result of total served orders for different request rates.

the served area. However, if the served area is more extensive, this may have a higher impact on the number of served orders. Another reason could be that the drone does not have to go back to the station after serving each request due to the high rate of requests.

Figure 6 shows similar trends to Figure 5 as the number of orders served means, proportionally, an increase in the profit generated, with regards to each strategy.

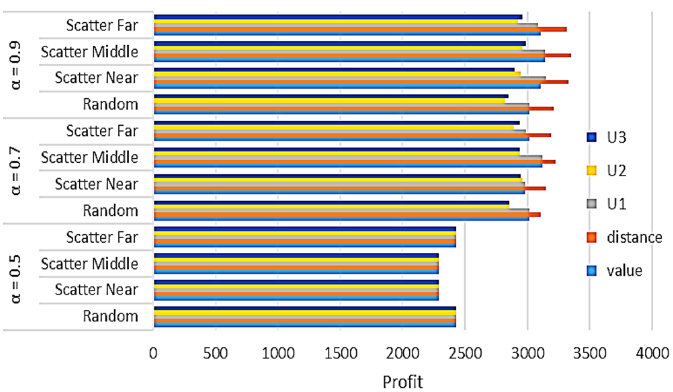


Fig. 6: Result of total generated profit for different request rates

However, more orders served for a strategy does not necessarily mean it also generates more profit. For example, for a scatter distribution with $\alpha = 0.9$, using $(U2)$ serve the highest number of clients but also generated the lowest profit. Moreover, although the number of clients served using the value-based strategy remains relatively constant with an increase in the rate of requests and orders, the profit is comparable to the other strategies.

A few noteworthy differences are that the profit generated plateaus after the rate of request of 0.7 i.e. the increase in the profits is not substantial between an α of 0.7 and 0.9. This could be that even if more orders are served, they are nearer and not necessarily of higher value. In addition, the distance is most strongly associated with the profits generated compared to the utilities and the number of high value orders served. This might be because the drone does not have to travel a significant distance to serve a client if there are available nearby orders. Therefore, if the drone is prioritising clients according to their proximity to its current location, then there is a high chance of serving more orders even with low values.

Figure 7 demonstrates the impact of different strategies on client satisfactions (i.e. satisfied, neutral, unsatisfied and disappointed) while varying the request rate.

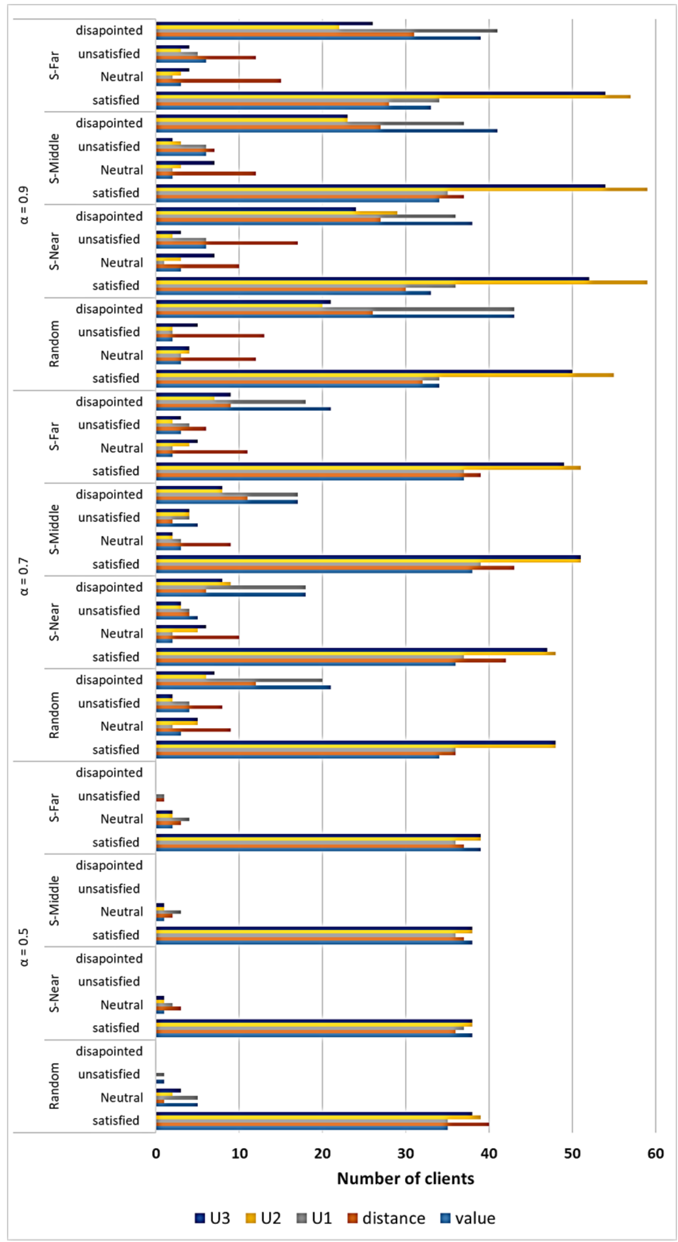


Fig. 7: Result of client satisfactions for different request rates and strategies (from a total of 100 clients).

The ratio of disappointed clients to satisfied clients increases with an increase in the rate of requests issued by clients. This could be because the clients have to wait longer when there is a large number of orders processed, and satisfaction increases with more drones, obviously. Also, the utility-based

$U2$ strategy seems best in serving the requests at increased request rates, while satisfying more clients.

Figure 8 shows the times that the drone spent at each state e.g., atStation, onRouteToClient, serving and onRouteToStation. If the drone spent more time at the station, this indicates that the drone is not fully utilised.

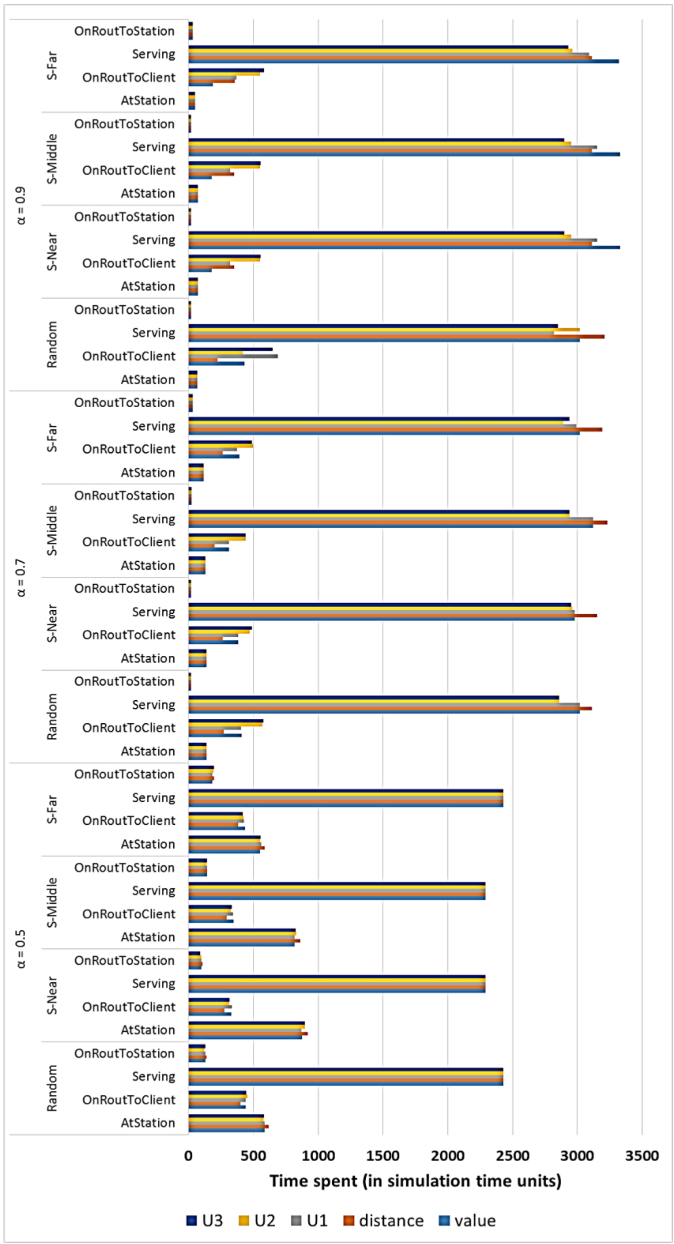


Fig. 8: Breakdown of time spent by the drone in each state for different request rates and strategies (the total duration of a simulation run was 4200 time units).

As the request rate increases, the time a drone spends at station decreases and vice versa. Also if the drone spent more time at the onRouteToClient state, this indicates that the drone was frequently changing target clients while on route to a client. As expected, the utilities $U2$ and $U3$ have the two highest time spent in the onRouteToClient state, as they attempted to balance between the value and the distance of each request, and could change decisions more often to serve a newer higher utility request while on route to a client - while on route to a client with the highest value or which is closest, there is less chance of a new request having higher value or being even closer. Under all scenarios, the drones were spending the maximum time serving, and little time at the station (except for $\alpha = 0.5$) this indicates that the drones were running at capacity and there were many orders to service.

IV. Conclusion

We have studied the trade-off between maximising revenue and maximising clients' satisfaction in the context of drone services. We have considered some possible drone strategies and identified common factors that may affect the decision-making process. A simulation study was done to compare different drone serving strategies. The client distribution does not matter significantly. With low-frequency requests, all strategies have similar outcomes. However, an increase in requests rate results in increased profit, orders served, but also higher clients' waiting times. A distance-based strategy generates slightly more profit in most situations than other strategies, whereas a utility-based strategy is the optimal choice regarding increasing served orders and more satisfied clients. The utility-based $U2$ and $U3$ are the most strategies associated with frequently changing target clients while on route to a client. We noted that the strategy that provides the most satisfied clients (e.g., $U2$) might not be the one that maximises profit (e.g., distance). Overall, there are clear trade-offs between maximising revenue and maximising clients satisfaction. Future work will involve working with multiple drones and different drone strategies. Also, we will consider other factors that may affect the on-drone decision-making process to increase reliability, efficiency and profitability.

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