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ORIGINAL ARTICLE

Drones-as-a-service: a simulation-based analysis for on-drone decision-making

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Abstract
Drone services are expected to emerge in many areas around the world in the near future and this is generating increasing interest. While there is a proliferation of ideas for various applications that can be delivered via drone services, the subject of drone service provisioning has received relatively less attention and, hence, is not well understood. We envision that a variety of drone applications (e.g. renting a drone as a security guard, to pick up and deliver something or to take an interesting photo) can be delivered as a service, using a common set of underlying service provisioning principles, such as making decisions as to whom to service next. In this paper, we study by simulation how different decision-making strategies for drones impact clients and service providers. In particular, the trade-offs between maximising provider revenue versus maximising a client's personal satisfaction, and different combinations of factors that influence drone behaviour (e.g. speed, distribution of clients, criteria for judging client requests, service duration, effect of battery and whether drones are allowed to change their target client on-the-fly) are investigated. This research has implications for scholars as well as drone service providers and application developers.

Keywords Drones · UAV · Drone services · On-drone decision-making · Clients' satisfaction

1 Introduction

Unmanned aerial vehicles (UAV), more commonly referred to as drones, are on the cusp of delivering a superior level of service to the general public, with a number of new companies in this area.[1] While some services are already up and running with drones acting as the means of delivery, countless others are being tested or researched. For example, the Metropolis project is developing a program to study the influence of airspace structure on different functions to accommodate more drones [23]. Other projects are developing Air Traffic Management (ATM) systems such as SESAR and NextGen [10]. 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.

For the customer of tomorrow, it is likely that drones may deliver food, packages and even medication. Drones have the potential to assist with all manner of tasks, from taking photos and providing security to aiding in disaster relief efforts and forecasting weather. As drone technology is beginning to take off and become more visible in day-to-day life, it remains to be seen how the customer's experience of drones can be improved and customer satisfaction can be maximised. On the side of drone technology, at present, work is being done to introduce new capacities that may allow drones to be more self-aware and autonomous [17, 27, 29]. In parallel, drones can be used to conduct different types of tasks in wide-ranging locations. The decision-making of drones needs to be designed in such a way as to allow drones to make decisions on the go. This requires,

[1]https://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/commercial-drones-are-here-the-future-of-unmanned-aerial-systems

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first of all, identifying all the factors that go into decision-making, managing all the constraints, the objectives and a hierarchical framework to deal with competing objectives. While the optimisation of a drone's decision-making is fairly well evolved [9], the optimisation of drone's decision-making in the context of service delivery is not. However, understanding the various aspects involved in decision-making at the service provisioning level is crucial to the successful adoption of drone applications at scale.

There are various aspects involved in the decision-making process in the context of service delivery. For example, drones could experience anomalies during flight, such as inner failure, changes in the environment or communication issues [27]. In dealing with such situations, decisions should be made in real-time on the drone itself while in flight, rather than from the station end. In a previous study [4], we showed that a drone can process tasks requiring no knowledge or intelligence when 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 client satisfaction by exploring the possible drone strategies and identifying some common factors that may affect the decision-making process. We use several stereotypical distribution patterns to cover different scenarios to assess the generality of the model. It is important to note that, in our simulations, the location of clients is fixed but this is initially unknown to the drone, and clients generate requests dynamically over time so that the locations of the next few requests cannot be anticipated. We conducted experiments to compare various techniques and to examine the difficulties with respect to service duration, mode of commitment, speed, the number of utility factors, client distribution, battery consumption and recharging. Recommendations are also made as to how these trade-offs can be managed such that customer satisfaction is prioritised and how decision-making processes may need to be implemented in order to ensure this. We modelled the on-drone-decision system as a multi-agent system where the drone (of the service provider) and each client (service receiver) are agents that interact with each other and react autonomously.

The main contributions of this paper are summarised as follows.

1. We identify the factors that play a key role in influencing drone behaviour and outcomes in drone service provisioning.
2. We propose a number of strategies that a drone could implement in order to maximise profit or client satisfaction.
3. We analyse the performance of each strategy against distinct objectives.
4. We evaluate the impact of different parameters to analyse the trade-offs between maximising profit and maximising client satisfaction.

This paper substantially extends the analysis given in the earlier work in [2]. The remainder of the paper is structured as follows. Section 2 reviews the current research on drone services. Section 3 introduces the concept of on-drone decision-making. Section 4 describes the systems design and Section 5 describes the experiments we have conducted, along with the results analysis. Finally, Section 6 summarises the research contributions and highlights areas for future work.

2 Related work

Over the past decade, there have been many studies on adopting the use of drones in civilian environments [5]. For instance, the use of drones has been explored for saving lives [12], delivering goods and medical supplies [25], surveying [24], filming [20], rescuing [19], building structures [13], pipe inspections [22], farming [7] and more. The idea of using a drone-as-a-service has been explored in various studies [11, 18]. An example of a recent application that presents the use of drones-as-a-service for business is the Google's project (Wing)[2] which was just has been approved by the Australian government in early 2019. Roldán et al. [16] use a drone to collect images in order to build a traffic map of the city, to manage traffic in real-time. Areias et al. [6] present a platform that provides an abstraction layer between the end-user and the drone to provide drones-as-a-service, allowing the end-user to communicate with the drone using high-level control operations to the platform. Urban Air Mobility projects with drone services which mainly focus on the delivery of parcels are becoming increasingly used in over 60 cities around the world.[3]

Although there are substantial advantages in using drones to deliver services, significant challenges need to be overcome in order to be fully adopted in business. Work has begun to look at security and network performance issues with UAV as a service [26]. The work in [15] looks at urban airspace traffic density estimations for drones. Also, the work in [1] explores drone service provisioning in an urban environment setting. However, this paper shows that the study of the impact of drone strategies on the service provider is still limited in the literature. This calls

[2] https://wing.com/intl/en_au/australia/

[3] https://www.unmannedairspace.info/urban-air-mobility/urban-air-mobility-takes-off-63-towns-cities-worldwide/

for new research and approaches to broaden new concepts and theories that may help the service provider as well as the service consumer to better predict the behaviour of the service as a part of a business process. Given the importance of a drone being able to apply different tactics, we implement an exploratory evaluation of several drone strategies in this paper. These initial results can be a part of evaluating the future of drone service provisioning in urban or rural areas.

3 The concept of on-drone decision-making

3.1 Overview

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

3.2 Drone

In our drone decision-making model, a drone acts as a single independent agent with limited power (lifetime). It has four main states: AtStation, OnRouteToClient, ServingClient and OnRouteToStation. These states are linked by different transitions to control the behaviour of the agent as shown in Fig. 1. Once the drone agent is created, initially it starts at the AtStation state and triggers the battery to start. Figure 2 depicts the battery transition during run time.

Suppose a drone is connected directly to the station centre and indirectly to clients to build awareness of the need for actions. Requests or instructions can be received by the drone at any state. However, the drone has to then decide whether it can take a job upon receiving a request from the station centre or an individual client.

A major factor that must be considered when handling incoming requests is the *affordability* of the service. In other words, can a drone fly to the target client, process the service and fly back to the station within its available lifetime? Affordability of service is one of the main factors affecting the utilisation of drones-as-a-service. In this context, a drone can afford to service a request while it has enough power to do so. If the drone cannot afford to service the received request, the require full charge (RFC) trigger will be fired which indicates that the drone has reached a low battery level and cannot service more requests. At this stage, it is necessary for the drone to go back to the station to re-charge. While a drone is recharging, it can receive order requests but these requests must be queued based on the followed strategy until the RFC is disabled. It is worth noting that while a drone is in the AtStation state, it is allowed to recharge regardless of the RFC trigger due to the fact that drone autonomous charging has now become feasible [28]. Each mission takes up the drone's time (travel time) in going from its current location (e.g. the station) to the client and back to the station, in addition to the time taken to service a single request (service duration).

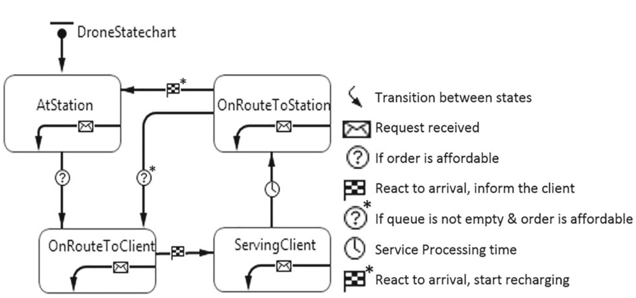


Fig. 1 Drone states

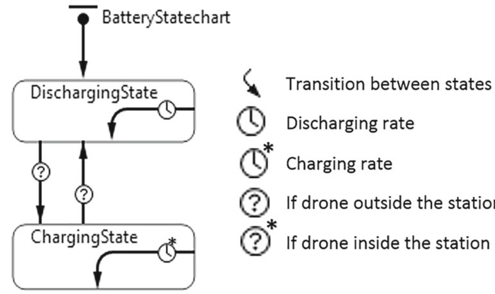


Fig. 2 Battery states

Franco et al. [14] explored the power consumption of drones. As most hobbyist drones use battery power as an energy source, the consumption and charging rates (here, the factor of 3 is simply due to observations of commercial hobbyist drone charging rates) can be calculated as in (1) and (2).

$$Consumption\ rate = \frac{1}{100 \times lifetime}\ per\ second \quad (1)$$

$$Recharge\ rate = \frac{Consumption\ rate}{3}\ per\ second \quad (2)$$

Depending on the type of service, sufficient speed can vary from one application to another. According to FAA's Part 107 rules,[4] the ground speed of small drones must not exceed 100 mph (160.9 km/h). Even with this generous limit, most small drones are not capable of flying at this speed. Drones flying at a higher speed may cause some safety concerns as well as consuming more energy than when flying at a lower speed [14]. Therefore,

[4] https://www.faa.gov/news/fact_sheets/news_story.cfm?newsId=22615

to accommodate different types of applications in our experiments, the drone speed is set between 60 and 100 km/h.

3.3 Client

A client can be an IoT sensor or a human with a smart device, located within the service area. In our model, we assume 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 the client issues a request based on a predefined rate (arbitrary request rate) as shown in Fig. 3.

The request rate can be classified into three categories, low, medium and high request rates. The value of these classifications may be affected by other model differences, such as service duration and drone speed. Each experiment clearly states the different rates prior to conducting the experiment. Each client is assigned a value that specifies how much money can be spent on a service. It also designates how much time is required for the service (service duration). We consider two types of service duration: short where client values range from 1 to 10, and long where client values range from 10 to 100.

How clients are distributed depends on the service area. We assume the service area where clients are distributed to be a square with a side length of L. A station can be located at the edge or inside the service area [4]. On the other hand, mapping clients across the service area is an essential measuring variable for the service provider. In order to deploy a number of clients in fixed positions, we consider various distributions. These distributions are random, scatter-near, scatter-middle and scatter-far as shown in Fig. 4, with the station at the left edge. Idle clients are depicted by a black circle. Once a client makes a request, the circle displays a red colour.

Every client issues requests independent of other clients, as illustrated in Fig. 5, and requests appear at different times. The arrow indicates the next client request, and the different snapshots indicate requests appearing at different locations at different time points, where the next request is generated randomly and is not anticipated by the drone. The figure also illustrates the process of clients requesting services during run time.

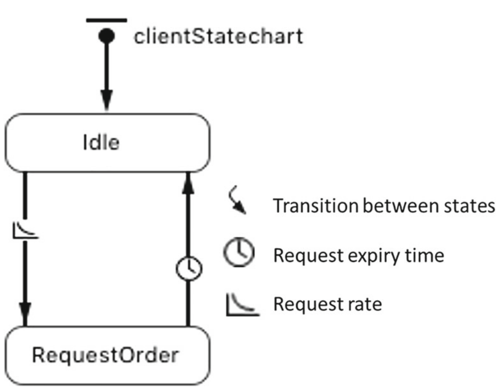


Fig. 3 Client states

At time t_1, the drone receives a service request from a client, the colour of the client, who issues the request, turned red. Then the drone responds to the request by moving towards the client's location. At time t_2, another request is received while the drone is servicing the first client. The drone queues the new request based on the acquired strategy. After servicing the first request the drone moves to the next scheduled location. At time t_3, the drone receives a higher value service request (based on the acquired strategy) from another client. Therefore, the drone changes its route to the new higher value client's location. As shown in Fig. 5, at time t_4, the drone has received two more requests but due to the low values of these two requests the drone continues making its way to the location of the current client. The process continues until the simulation reaches t_n which is the end time of the simulation.

Client satisfaction is a key measurement variable for service provisioning. Longer waiting times are often associated with relatively lower customer satisfaction. Figure 6 shows the various scenarios and the associated client satisfaction levels in our model. Client satisfaction levels can range from excellent to good to poor, depending on 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 is associated with satisfaction. Clients find the service to be excellent if the waiting time is less than satisfaction rate δ and good 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.

4 Experiment design

4.1 Overview

The process of determining which task a drone should service 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. the minimisation of waiting time, or the maximisation of profits. This section presents the various parameters involved in the decision-making process following objective functions, which are used to design our experiments.

Our study simulates a drone servicing clients with requests/tasks in simulated time corresponding to a (real-world) 1-h period (so that the effects of battery life are temporarily suppressed for simplicity, assuming 1-h battery

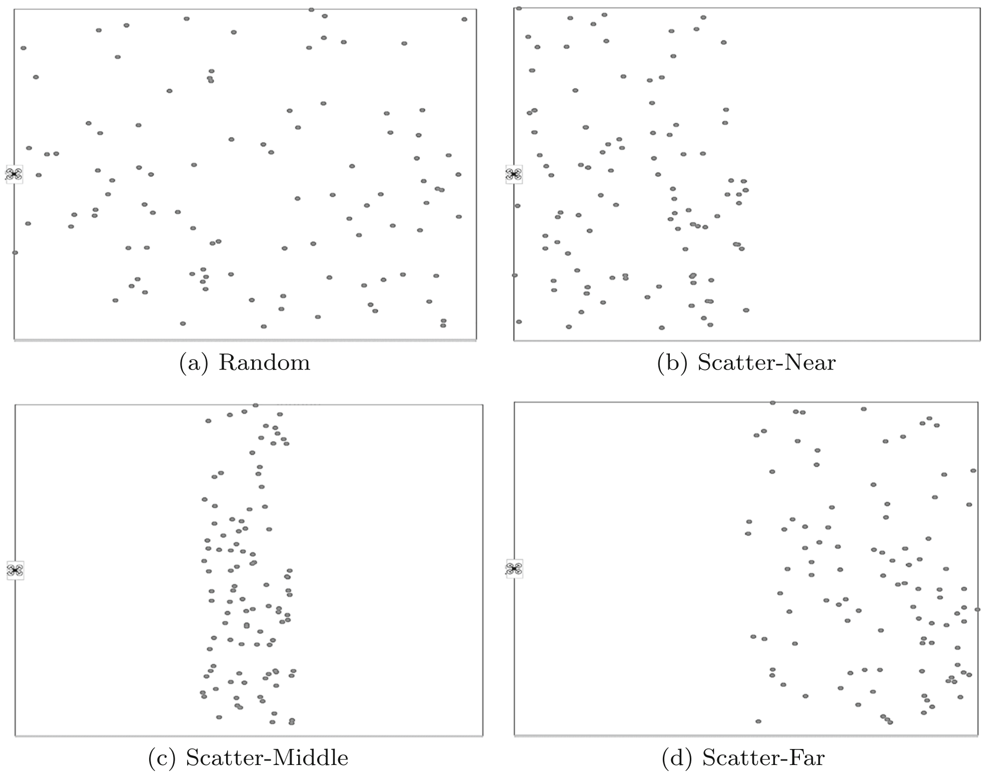


Fig. 4 Client distributions

life is not inconceivable for future drones). We study the system behaviour focusing on the number of serviced requests, total revenue generated, client satisfaction and the time that the drone spends in each state.

4.2 Factors in the choice of which request to service

This section describes various factors involved in decision-making in the context of service delivery. These are general factors that a service provider should consider, regardless of the delivery method. For example, the distance from one location to another is an important factor. If a client makes a request, the service provider needs to know the location of the client to determine the optimal route. However, finding the route depends on the delivery method (e.g. using a bike, car or drone). Therefore, depending on the delivery method, the distance varies constantly. Although all delivery methods need to know the distance to the client, the distance varies constantly for each method. Factors in decision-making in the context of drone services delivery include:

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

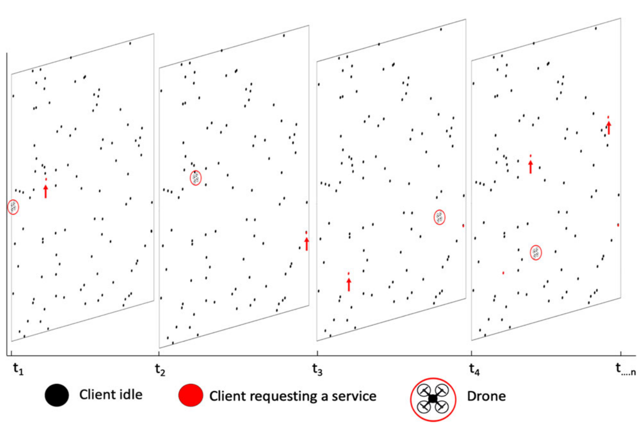


Fig. 5 A snapshot of service requests issued by clients during run time at different time frames

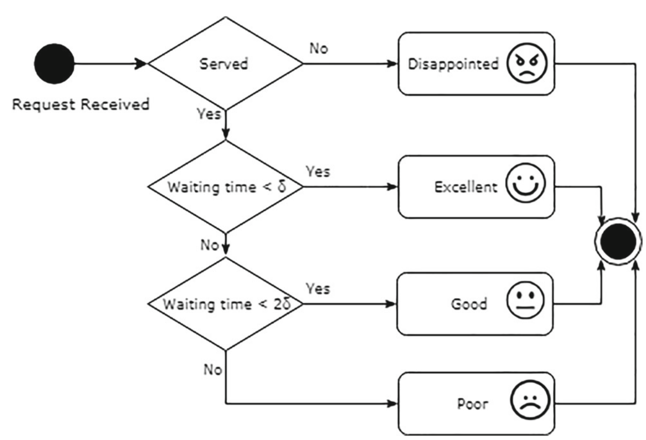


Fig. 6 Relationship between waiting time and satisfaction level of the client

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 to completion, 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 number 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 the case of high-value service requests, e.g. while on the way to a client, a drone can decide to change its mind and go after a higher value request.
- *Fairness*: Orders are received by the station or the drone at the time of their submission, which then may initiate the service process. This time is critical for both the drone and the clients as it leads to managing the sorting and the waiting times. For example, in order to maintain fairness in the queuing scheme, the drone may consider servicing orders based on their arrival time.
- *Other factors*: There are other factors that need to be considered in the decision-making process. The range in this context is not defined as the distance that the drone is able to cover with the available battery life, but the maximum distance that the drone needs to be away from its controller before it loses connectivity with its controller. While there are a lot of drones which no longer need to be in the proximity of the controller, there are still some which need to be within range of their controllers [21]. In our simulated study, we assume that all drones are within communication range of their station.

Another important factor in drone decision-making is the amount of data storage and processing capacity that is required for 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 can be natural factors such as temperature, pressure, visibility and humidity; or other 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 environmental factors for a number of reasons, some of which are to prevent damage to itself, to ensure the quality of the task to which the drone has been assigned and to ensure the legality of the operation. In this study, we assume that drones operate with no environmental restrictions (which would affect our results). Figure 7 shows the main variables used for building the model.[5]

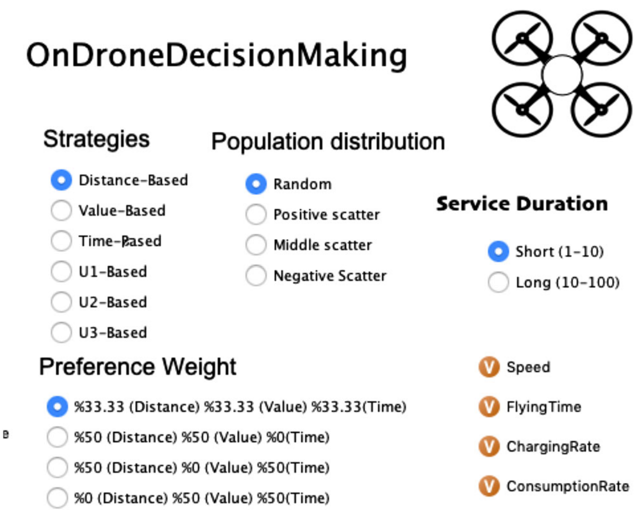


Fig. 7 Main parameters used in the simulation

4.3 Study objectives

Drone service providers may operate with many end-goals (objectives) in mind. For the purpose of the experiment, we consider the following objectives:

- Maximising the number of serviced orders
- Maximising revenue
- Maximising client satisfaction
- Minimising client waiting time

4.4 Strategy implementation

We explore various on-drone strategies to enhance drone service delivery. We specify a study area with (L = 1000 m), a station located at the edge and clients distributed randomly. The steps in running the simulation are as follows: 100 clients periodically send requests to the station at different average rates α per hour. Unless otherwise stated, a drone has a speed, a processing time of v and a battery life of 1 h. 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

[5]The complete source code is available at https://drive.google.com/open?id=1xXqUk5GilWmj-CUj8nxVeem6hZ45pb5K

no orders in the queue. If the drone's battery is insufficient, the drone will go back to the station for recharging and the upcoming request will be queued until the drone is fully charged.

In our experiments, we study the effect of three main factors: distance (i.e. between the drone and the client), value (financial incentive) and time (first come first serve) in building the drone's strategies for handling the upcoming requests. Each order comes at a specific time (t), has a value (v) and a determined distance (d) between the current drone location and the requesting client.

Suppose a client is located at position L_c and the drone's current position is denoted as L_d. For the experiments, we assume that the threshold for satisfaction is $\delta = 600$ s. For each received order request r, there is a value $v(r)$ and a distance which is calculated using Euclidean distance, as follows: $d(r) = \sqrt{(L\_c_x - L\_d_x)^2 + (L\_c_y - L\_d_y)^2}$.

4.4.1 Rules

A drone can receive requests in any one of the drone states (see Fig. 1). We formulate the following rules to dictate how the drone should respond to a request received in each state:

1. If the order is received while the drone is *at the station* and the order is *affordable*—the drone will go to the client
2. If the order is received while the drone is *servicing* another order—the drone will add the order to the orders list.
3. If the order is received while the drone is *going back to the station* and the order is *affordable*—the drone will go to the client.
4. If the order is received while the drone *en route to a client—decision required*
5. If the drone finished servicing the current order but the *order list is not empty—decision required*

Note that, in this context, the phrase *decision required* means that a decision as to which strategy to employ is needed.

4.4.2 Preference measurement: scales, preference and utility

Different factors play different roles toward influencing drone behaviour and performance outcomes in drone service provisioning as discussed in Section 4.2. In this paper, the focus is on the following factors: distance, value and time of arrival for each received order. In this context, below, scaling refers to allocating normalised values to the different factors, in order to decide which order to serve next.

Distance scale (dS) As mentioned previously, 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 this as shown in (3):

$$dS(r) = \frac{d(r)}{d_{max}} \tag{3}$$

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 request r ($v(r)$) by v_{max} to standardise the value of the current job as in (4), where v represents the value of the order that has been received:

$$vS(r) = \frac{v(r)}{v_{max}} \tag{4}$$

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

Time scale (tS) Within the simulator, the order comes at a certain time unit $t(r)$ and then stops at a predefined time unit $tmax$. Therefore, in order to scale each order based on the time of the arrival, we calculate this as shown in (5):

$$tS(r) = \frac{t(r)}{t_{max}} \tag{5}$$

Preference weights (w) Preferences or priority values for distance (w_d), value (w_v) and time (w_t) are weighted equally in our simulation study (though other weights can be experimented with), where:

$$w_d + w_v + w_t = 1 \tag{6}$$

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 use (3), (4) and (6) to formulate the utility function as shown in (7).

$$U(r) = w_d \cdot dS(r) \;+\; w_v \cdot vS(r) \;+\; w_t \cdot tS(r)) \tag{7}$$

4.4.3 Strategies

We conducted a set of experiments to assess the decision-making process, considering three factors: distance between the drone and the client, value of the request and time of request arrival. Decisions are made to meet the purpose of rules 4 and 5 as discussed in Section 4.4.1. Five strategies are considered when deciding which order/request to service next.

Distance-based (*argmin*) Clients in closer proximity are preferred to be serviced first. A drone can find the nearest client (by geographical location) 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, we apply (8) for both rules.

$$argmin_{r\in\mathbb{R}}(d(r)) \tag{8}$$

Value-based (*argmin*) Orders with a higher value are preferred to be serviced first. Drone queue orders in a descending order based on their values. Choosing this strategy means that the drone always applies (9) when it performs a regular check (i.e. on the order list) after each service or as soon as it receives a new order.

$$argmin_{r\in\mathbb{R}}(v(r)) \tag{9}$$

Time-based (*argmax*) Orders that come first are preferred to be serviced first. Drone queue orders based on their arrival times, using the first come first serve approach. This allows the drone to be more committed by prioritising orders based on their arrival time. As with previous strategies, a drone always applies the strategy pattern, here (9), when it performs a regular check after each service or as soon as it receives a new order.

$$argmin_{r\in\mathbb{R}}(t(r)) \tag{10}$$

Utility-based (*U*1) In this strategy, there are two cases to consider. First, if an order (or request) is received while the drone is on its way to another order which we call the current order (r'), then the received order r will be compared only with r' for rule 4 in terms of distance, value and time using the scale values and preference value from (3), (4), (5) and (6) respectively as shown in (7). Then, r is serviced first if $U(r) > U(r')$; otherwise, r' is serviced. Second, if the drone has finished servicing the current order but the order list is still not empty, let r' be assigned to the shortest distance order using (8), let r'' be assigned to the highest value order using (9) and let r be assigned to the first arriving order using (10). The same applies again as in the first scenario, i.e. we compare $U(r' = argmin_{r\in\mathbb{R}}(d(r)))$, $U(r'' = argmax_{r\in\mathbb{R}}(v(r)))$, and $U(r = argmin_{r\in\mathbb{R}}(t(r)))$. For either of the scenarios above, the order with the highest U is serviced first in line with for rule 5.

Utility-based (*U*2) 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 (7). The order with the highest U at the time r is received is serviced next, again for both situations in rules 4 and 5.

Table 1 Experiment parameters

Parameter	Value
Simulation total run time	3600 s
Request rates	2, 3 and 4 requests (per h)
Drone speed	60 km/h
Drone life time	3600 s
Drone mode	Adaptive
Service duration	Short
Number of utility factors	3
Client distribution	Random

Utility-based (*U*3) This strategy is a combination of $U1$ and $U2$; it uses different actions for each rule. If the order is received while the drone is flying to a client, the drone uses $(U1)$ to fulfil rule 4. As for rule 5, the drone uses $(U2)$ to determine the next request to service. 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 computation compared to $U2$.

5 Experimental results and discussion

The simulations were run with Anylogic[6] software for various combinations of drone strategies, speed, service duration and for different request rates α. As mentioned previously, a drone can follow many strategies but only six strategies are tested here. Experiments are built on previous work [2] which investigates the effect of two factors on building drone strategies with a fixed speed and service duration. This work introduces a new level of decision-making by adding one more factor to the previous ones and changing the utilities accordingly. Extending the work in [2], we describe sets of experiments using different techniques and parameters with their default values in Table 1. We also study the effect of various parameters including service duration, committed mode, drone speed, the number of utility factors, client distribution, battery constraints and recharging.

In describing the following experiments and results, we use the following measures:

Number of serviced orders This represents how many orders were serviced by the drone during run time.

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

Profit This is a measure of the total profit generated from the serviced orders.

Average waiting time The total average time that the clients spend waiting for the drone's arrival after issuing a request.

Number of decision changes This measures the number of changes that a drone makes while travelling to a client.

The level of clients' satisfaction Excellent, good, poor or disappointed

5.1 Initial experiment

This experiment aims to address a number of areas of interest from the perspectives of orders serviced: total profit generated, number of decision changes and the level of client satisfaction respectively, as shown in Fig. 8. Figure 8a shows that, as expected, a maximum number of orders are serviced when the rate of requests is the maximum (i.e. 4), simply because there are more requests (and within the capacity of the drone).

Also, with low-frequency requests, all strategies have similar outcomes. All utilities and the distance strategies are also highest under these scenarios compared to lower rates of requests. However, the number of clients serviced using the value-based and time-based strategies remains relatively constant with an increase in the rate of requests, i.e. α.

For the pure value-based strategy, this is most likely due to the drone being constrained by servicing high-value clients who might be a distance from the drone. If the high-value clients are widespread, the drone will have to travel further to service those clients, which could result in servicing the same number of clients but generating more profit, as shown in Fig. 8b. It can be seen that using the time-based strategy to increase fairness could result in servicing a constant number of orders and generating a constant amount of profit as the drone is running at full capacity because it services the requests which arrive first and travels greater distances.

Figure 8b shows similar trends to Fig. 8a as the number of orders serviced means, proportionally, an increase in the profit generated, with regard to each strategy. When a strategy services more orders, this does not necessarily mean it generates more profit. For example, when using the time-based strategy with α = 3, the drone serves a higher number of clients than the value-based strategy but also generates the lowest profit. Although the number of clients serviced using the value-based strategy remains relatively constant with an increase in α, the profit is comparable to the other strategies.

The clients' waiting time is an important measure of the quality of drone services as it is directly related to client satisfaction. Longer waiting times are often associated with relatively lower customer satisfaction [8]. Figure 8c shows the average client waiting time for each strategy. All strategies seem to maintain a similar average waiting time for low α but as α increases, the average waiting time for value-based and time-based strategies escalates dramatically. However, distance-based and $U1$ strategies tend to have the lowest average waiting time with a slight increase when using $U2$ and $U3$. This indicates that the distance-based and utility strategies are better for minimising the average waiting time for this scenario.

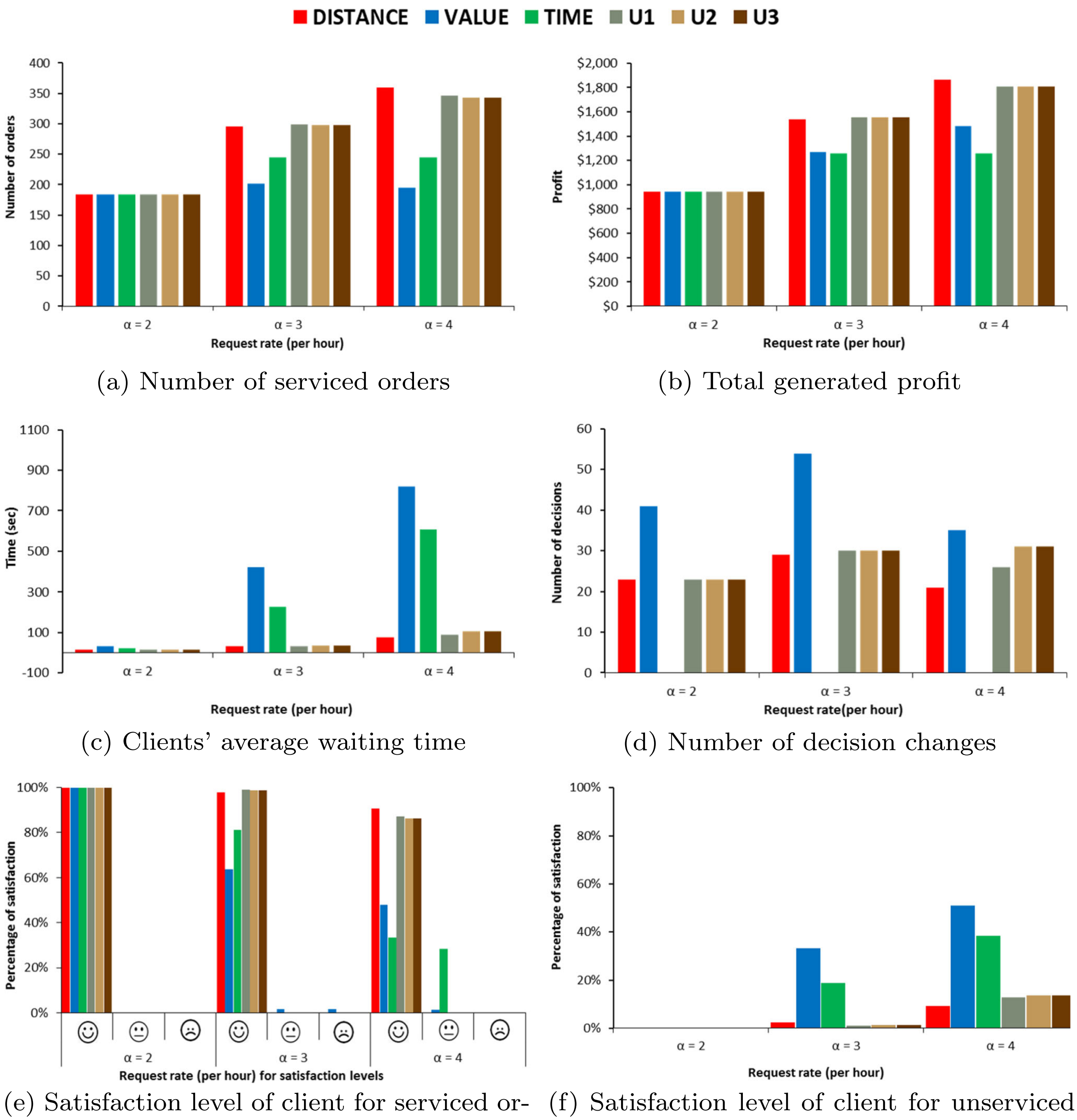
In relation to the number of decision changes, the value-based strategy resulted in the highest number of decision changes as shown in Fig. 8d. These are indications of cooperation and adoption by the drone while in the onRouteToClient state. This cooperation might have a negative effect, i.e. an increase in the number of changes means spending more time onRouteToClient and this may result in minimising the number of serviced orders.

Figure 8e and f demonstrate the impact of different strategies on client satisfaction levels (i.e. excellent, good, poor and disappointed) while varying the request rate. The ratio of disappointed clients to satisfied clients increases with an increase in the rate of requests issued by clients. This could be because clients have to wait longer when a large number of orders are being processed. Also, the distance-based strategy seems best in servicing requests which arrive at an increased rate while satisfying more clients.

The distance-based strategy is most strongly associated with the profits generated compared to the utilities, time and value. This might be because the drone does not have to travel a significant distance to service a client if there are available nearby orders. Therefore, if the drone is prioritising clients according to their proximity to its current location, there is a high chance of servicing more orders with low values. When α is high, the time-based strategy scores the lowest percentage of excellent satisfaction compared to the other strategies but it also scores the highest percentage of good satisfaction level.

A comparison of the excellent satisfaction for the time-based and the value-based strategies shows that both score a low percentage but each impacts other parameters, for example, the value-based strategy increased the profit gain whereas the time-based strategy increased good satisfaction. The time-based strategy is most strongly associated with the satisfaction level of good and poor due to its function, whereas other strategies result in more satisfaction levels of excellent and disappointed.

Note that due to the relatively low number of clients with a satisfaction level of good and poor for most strategies, the rest of the experiments will only demonstrate the results for the satisfaction levels excellent and disappointed.



(a) Number of serviced orders

(b) Total generated profit

(c) Clients' average waiting time

(d) Number of decision changes

(e) Satisfaction level of client for serviced orders

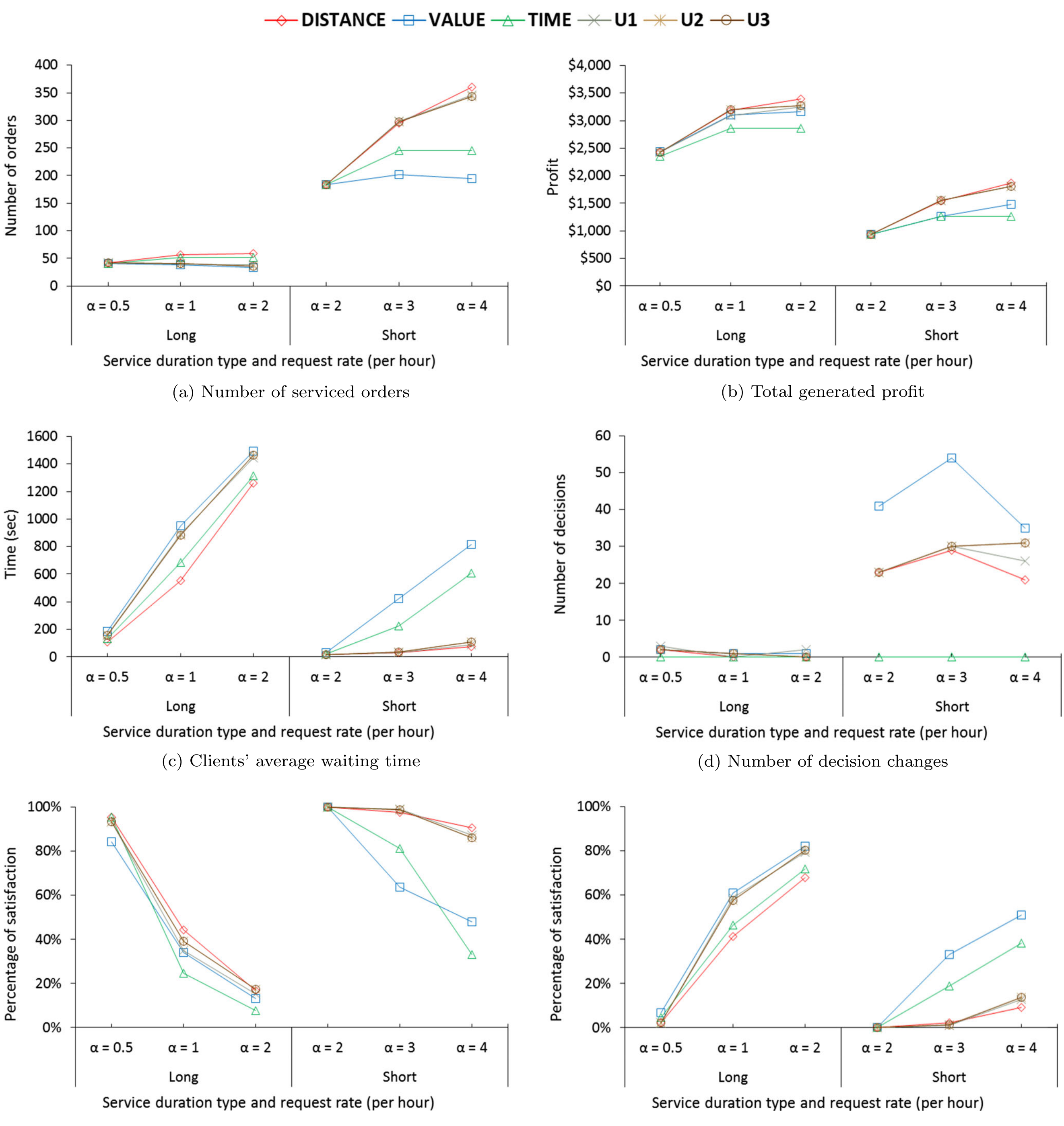
(f) Satisfaction level of client for unserviced orders

Fig. 8 Experiment results for different measures

5.2 The effect of service duration

This section explores the impact of service duration on the measures discussed in Section 5.1 for drone services. As stated earlier, each client has been assigned a value that specifies the cost and time required for the service. In this experiment, the long service duration values range from 10 to 100, along with a range of new values for α [0.5, 1 and 2]. Then, the results are compared with the experiment discussed in 5.1 which utilised the short duration approach. The reason for applying different values for α in this experiment is that α is critical in determining the performance of each strategy. Using a low value of α for short service duration does not necessarily mean it has the same level of being low for long service duration. Nevertheless, a midpoint has been used for both approaches, where $\alpha = 2$, to show the sensitivity of these two variables with respect to the other variables.

The impact of the change of service duration is shown in Fig. 9. This figure demonstrates the performance of each strategy using different measures. Although there is a clear correlation between the increase in α and the number of received orders, the length of service duration has a significant effect on the number of orders that can be serviced. For a long service duration, the number of serviced orders plateaus after $\alpha = 1$ but the profit generated slightly increased as shown in Fig. 9a and b. However, the increase in the profits is not substantial between $\alpha = 1$ and 2. The reason for this could be that the drone is already operating at full capacity and servicing higher value orders. The results



(a) Number of serviced orders

(b) Total generated profit

(c) Clients' average waiting time

(d) Number of decision changes

(e) Percentage of clients rating the service as excellent

(f) Percentage of clients rating the service as disappointing

Fig. 9 The effect of service duration also show that there is an inverse relationship between the number of serviced orders and the total profit generated for both service durations. A noteworthy observation is that dealing with long duration services can result in servicing fewer orders but generating higher profit and vice versa for short durations.

As a consequence, for long durations, the average waiting time is related to the frequency of orders in the form of a negative linear trend for all strategies with longer waiting times as α increases, as shown in Fig. 9c. On the other hand, all strategies except value and time-based strategies maintained low average waiting times for short durations as α increases. This behaviour has a correlation with the percentage of disappointment as shown in Fig. 9f and an inverse correlation with the percentage of satisfaction as shown in Fig. 9e.

The results in Fig. 9d show that when using the short duration approach, the drone changes more decisions while en route to the client than the long duration approach. This is due to the fact that for short durations, the drone spends less time servicing individuals but more time travelling to clients.

Overall, the distance-based strategy is most strongly associated with servicing more orders, generating more profit, minimising the average waiting time and eliminating disappointment for both short and long service durations. Also, the time-based strategy serviced more orders than the utilities in the long duration but generated the lowest profit. Although the utilities performance of servicing orders dropped, their generated profits are comparable to the other strategies.

5.3 The effect of the committed mode

The aim of this experiment is to compare the results in Section 5.1, where the drone was in an adaptive mode, with the results of the drone being committed as shown in Fig. 10.

In this context, a committed drone is one which does not change its decision if a new request is received while travelling to service a client. This means that if a higher value order arrives while the drone in the onRouteToClient state, it will be queued and the the drone will proceed to the current order. In other words, the committed drone skips rule 4, as mentioned in Section 4.4.1, and no decision needs to be made.

From the perspective of the requests serviced, the following observations are made (see Fig. 10b). With low α, all strategies seem to service the same number of orders, and with medium α, committed was better using the value-based strategy and there were slight changes when using other strategies. However, as α reaches a high level, adaptive was better using the distance-based strategy but committed was better using the utilities-based strategies. The time-based strategy remains the same for both modes as it is already committed to servicing orders based on their time of arrival.

From the perspective of the profit generated, the following observations are made. Figure 10b shows similar trends to Fig. 10a as the number of orders serviced are proportional to the profit generated in regard to each strategy.

Figure 10c shows the clients' average waiting time for each strategy for both types of drone modes. The clients' average waiting time increases with an increase in α for both adaptive and committed scenarios. However, the clients' waiting time under the adaptive scenario is slightly lower, especially for the utility and the value-based strategies. This indicates that the adaptive mode is better for minimising the waiting time. The committed drone does not change any decisions at all, as shown in Fig. 10d.

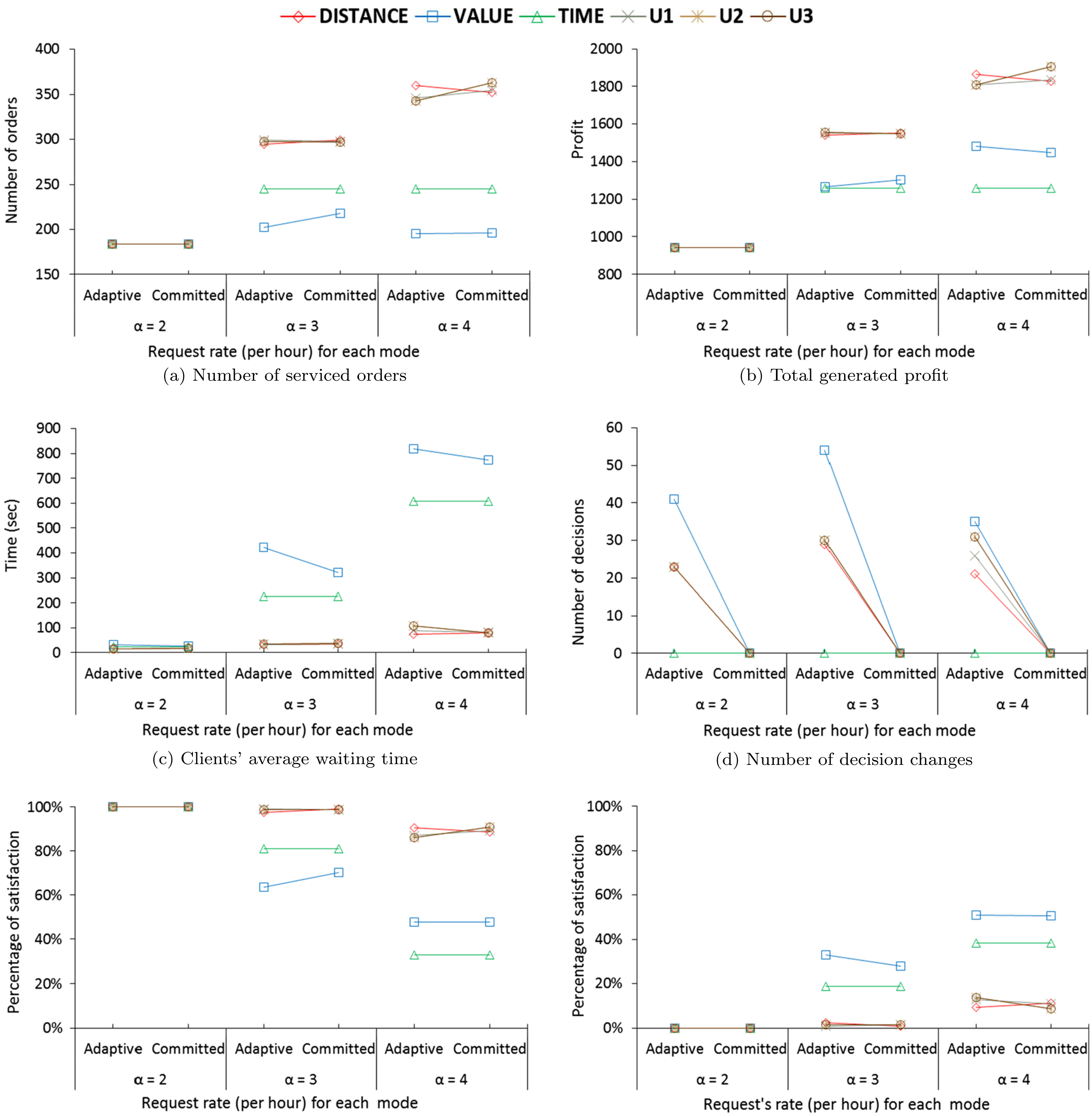
Finally, from the perspective of client satisfaction, Fig. 10e shows that the utility and the value-based strategies increase the percentage of client satisfaction at an excellent level but this decreases for the distance-based strategy decreases it under the committed mode. Moreover, the utility and the value-based strategies decrease the percentage of disappointed clients but the distance-based strategy increases it under the committed mode as shown in Fig. 10f. This suggests that if the station assigns requests to a drone based on proximity to the requests, the drone needs to be adaptive. However, if the station assigns requests to the drone based on utility, the drone needs to be committed.

5.4 The effect of drone speed

In order to evaluate the impact of drone speed on this system, we used the same parameters as in Section 5.1, except the drone speed is increased to 100 km/h. Figure 11 demonstrates the impact of drone speed using various measures.

Figure 11a shows that the number of serviced orders increase as α increases. The results clearly show that an increase in drone speed has a larger impact on the value-based and time-based strategies. This gives an indication of the impact of the drone travelling at a higher speed while servicing requests based on the highest value or the first-come-first-serve (or pure time-based) approach.

With regard to the total generated profit, Fig. 11b shows similar trends to Fig. 11a as the number of orders serviced is proportional to the profit generated with regard to each strategy. The clients' waiting time decreases with an increase in drone speed as shown in Fig. 11c. Figure 11c



(a) Number of serviced orders

(b) Total generated profit

(c) Clients' average waiting time

(d) Number of decision changes

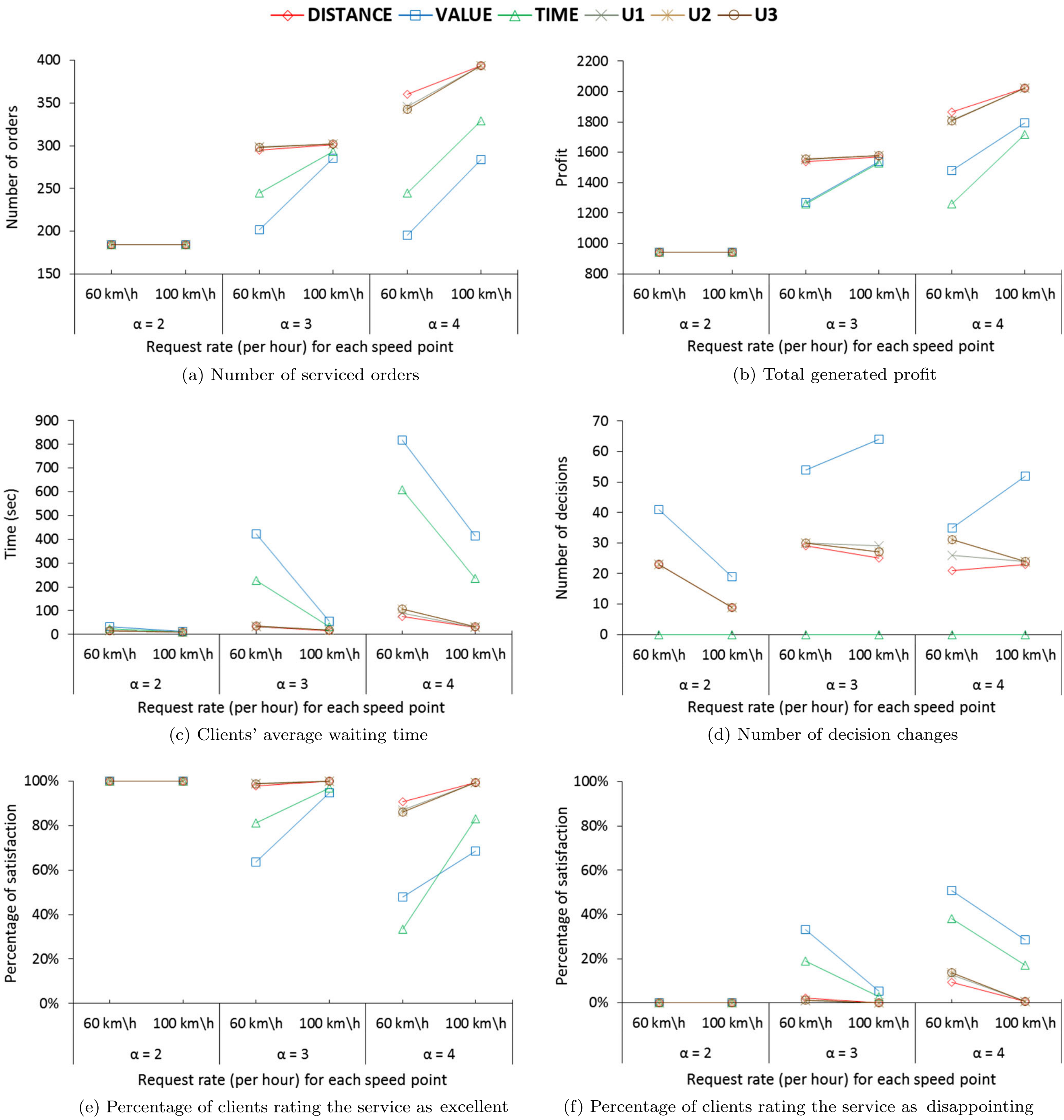
(e) Percentage of clients rating the service as excellent

(f) Percentage of clients rating the service as disappointing

Fig. 10 The effect of committed mode

illustrates that when the speed of the drone increases, the average waiting time decreases correspondingly. This shows there is a strong relationship between drone speed and clients' average waiting time.

There is a clear relationship between drone speed and the number of decision changes, where the number of decision changes decreases as drone speed increases for different values of α as shown in Fig. 11d. This signifies that when travelling at a higher speed, the drone spends less time en route to the client, and more time servicing requests, as one would expect. Furthermore, increasing the speed positively impacts the number clients satisfied at the excellent level and disappointed clients, as shown in Fig. 11e respectively. However, increasing the speed is a controversial solution mainly due to safety issues related to the drone itself and the available infrastructure.



(a) Number of serviced orders
(b) Total generated profit
(c) Clients' average waiting time
(d) Number of decision changes
(e) Percentage of clients rating the service as excellent
(f) Percentage of clients rating the service as disappointing

Fig. 11 The effect of drone speed

5.5 The effect of the number of utility factors

In this experiment, we study the effect of varying the number of factors used to make up the utility function. Figure 12 compares the use of two- and three-factor utilities using a range of measures. Our previous work in [2] considers the use of two factors (i.e. the distance and value of the received request) in modelling the utility-based strategies, whereas this work adds one more factor to balance between distance, value and time of arrival for each request.

For all measures (from Fig. 13a to f), the results are similar on all fronts with using the two-factor utility; however, there is a slight positive change with a high value

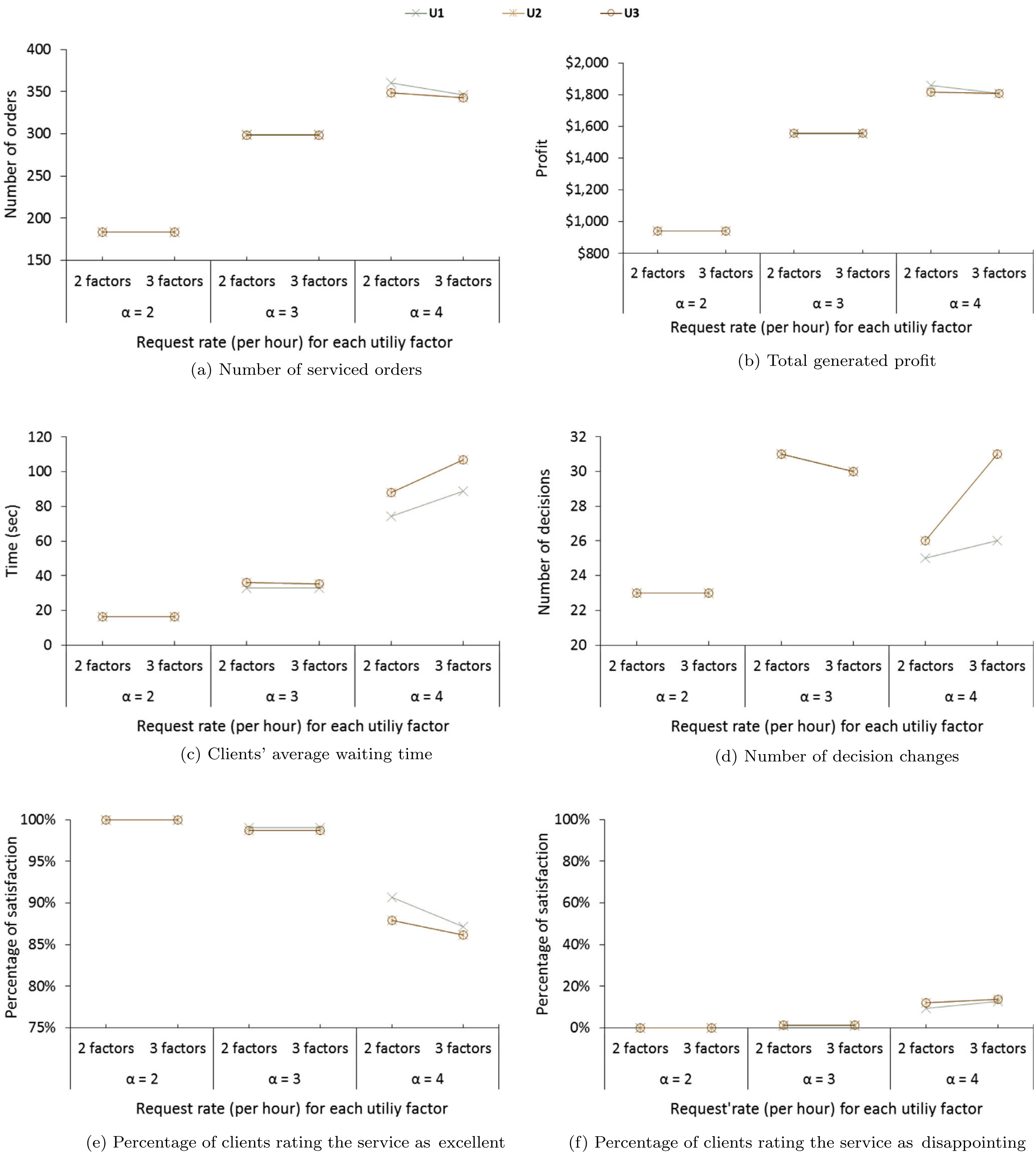
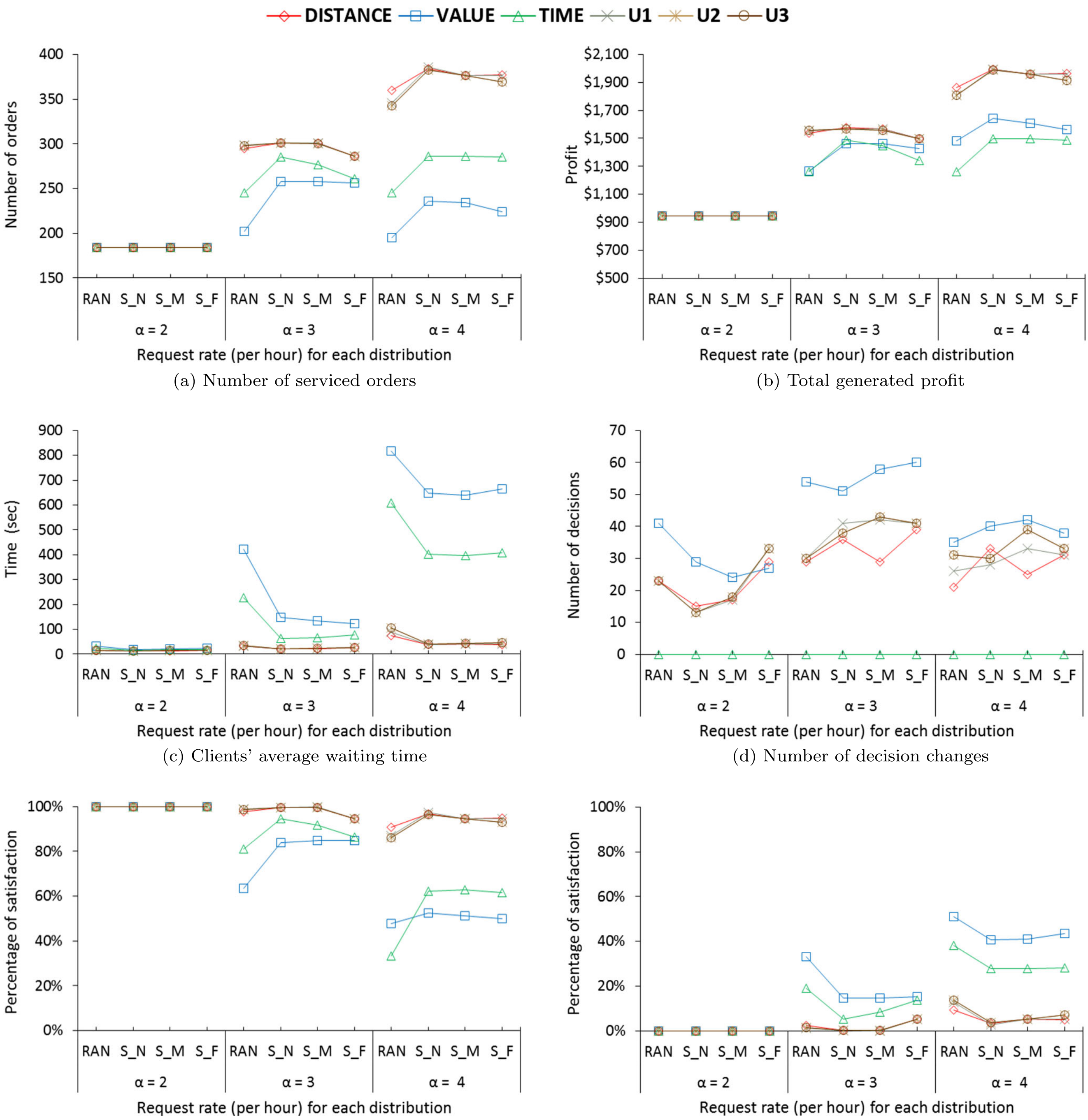


Fig. 12 The effect of the number of utility factors

of α. The reason for this is that the time-based strategy's performance was not significantly better with a high α as shown in Section 5.1. This possibility is more probable, due to the fact that it has not contributed to improving the performance of the utility-based strategies.

The main objective of combining more factors into the utility function is to maintain dynamic stability during the servicing operation. However, with the given parameters, adding time as a third factor did not enhance the performance.



(a) Number of serviced orders
(b) Total generated profit
(c) Clients' average waiting time
(d) Number of decision changes
(e) Percentage of clients rating the service as excellent
(f) Percentage of clients rating the service as disappointing

Fig. 13 The effect of clients' distribution

5.6 The effect of client distribution

Client distribution may play a critical role in either upgrading or downgrading the performance of each strategy.

In this experiment, clients are distributed differently, i.e. random, scatter-near, scatter-middle and scatter-far as discussed in Section 3.3. Figure 13 illustrates the performance of each strategy on the four distributions from different aspects.

For all measures (from Fig. 13a to f), the results are similar on all fronts with a varying client distribution except for a slight negative change with the random distribution. The reason for this is 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 the serviced area. However, if the serviced area is more extensive, this may have a higher impact on the number of serviced orders. Another reason could be that the drone does not have to go back to the station after servicing each request due to the high rate of α. There are a few noteworthy differences, such as the number of serviced orders slightly decreases as the distance of the scattered distribution increases. For example, when using the value-based strategy with $\alpha = 4$ for the scatter-near distribution, a higher number of clients are serviced than when using the scatter-far distribution and it also generates a higher profit. On the other hand, the number of decision changes increases as the distance of the scattered distribution increases except for a high α where the strategy changes are almost equal. Distance-based and utility-based strategies serviced a significant number of orders with all distributions compared to time-based and the value-based strategies, and this generated a significant amount of profit. This also has an impact on the percentage of clients which experienced an excellent level of satisfaction and disappointment. Overall, there is a clear correlation between the number of serviced orders and client distribution. The strength of this correlation is significant when applying the value-based or time-based strategies. The distance-based and utility-based strategies have a comparable performance for all distributions. Although using different scales of distribution may affect the overall performance, all scattered distributions have a quite a similar impact with respect to their distance from the station.

5.7 The effect of battery constraints and recharging

The aim of this section is to explore the impact of battery capacity and recharging times on the performance of the servicing strategies. Table 2 shows the parameters for these experiments. In Section 5.2, we studied the impact of different service durations without considering the impact of battery constraints. In this section, we run two different types of experiments under limited battery capacity: the first focuses on a long service duration where $\alpha = 0.1, 0.3, 0.5$, and the second focuses on a short service duration where $\alpha = 0.5, 0.7, 0.9$. The results for both experiments are shown in Fig. 14, comparing the performance of each strategy for different measures. We noted that with low α, all strategies have a similar performance for both short and long service durations with respect to their outcomes as related to their inputs. Also, we noted that some strategies managed to maintain their sense of efficacy and sustained a higher level of performance compared with other strategies, such as the value-based strategy.

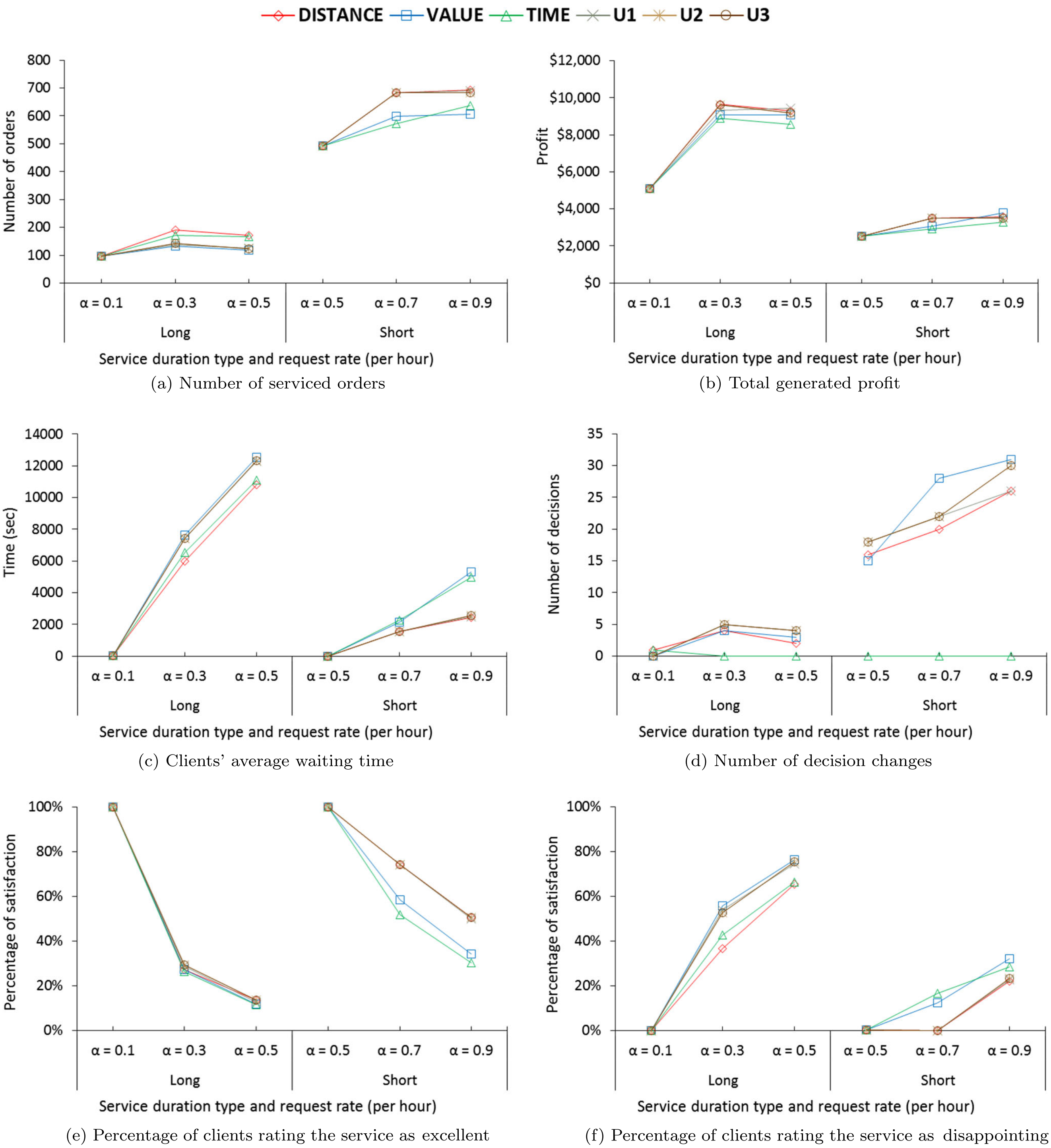
Table 2 Experiment parameter

Parameter	Value
Simulation total run time	36,000 s
Service duration	Short and long
Request rates	0.1, 0.3 and 0.5 request (per hour) for short service duration
	0.5, 0.7 and 0.9 request (per hour) for long service duration
Drone speed	60 km/h
Drone life time	3600 s
Drone mode	Adaptive
Number of utility factors	3
Clients distribution	Random

From the perspective of the requests serviced, the following observations are made (see Fig. 14a). For long service duration, the distance-based and time-based strategies serviced the highest number of clients, whereas the distance-based and utility-based strategies serviced the highest number of clients for a short service duration. The number of serviced orders slightly decreases with high α for a long duration but this is not true for a short duration. This could be because there is a high chance of more new requests with a higher value or being far away with respect to the drone. This also indicates that the drone was running at capacity and there were many orders to service. This behaviour negatively affected the profit gain as shown in Fig. 14b.

In regard to the generated profit, for a long service duration, the distance-based and the utility-based ($U2$ and $U3$) strategies generate the highest profit with medium α, whereas the utility-based ($U1$) strategy generates the highest profit with high α. For a long service duration, the distance-based strategy and the utility-based strategy generate the highest profit with medium α, whereas the value-based generates the highest profit with high α. Noteworthy observations are as follows: from medium to high α, all the strategies generated profit plateaus for both experiments except for two strategies; $U1$ for a long duration and the value-based strategy for a short duration. Both strategies generate significant profit with high α. This indicates that, if the service duration is long and the request rate is high, the utility-based strategy ($U1$) is the best. On the other hand, if the service duration is short and the request rate is high, the value-based strategy is the optimum option for profit maximisation.

Figure 14c shows the clients' average waiting time for each strategy for short and long service durations. With a low value of α, the results show that all strategies appear to have a very minimal waiting time. Due to the large difference in the time of service, the average waiting time followed a steep upward trajectory for a long duration. As



(a) Number of serviced orders
(b) Total generated profit
(c) Clients' average waiting time
(d) Number of decision changes
(e) Percentage of clients rating the service as excellent
(f) Percentage of clients rating the service as disappointing

Fig. 14 The effect of battery and recharging

we are not only interested in the time of service, our major concern is the performance of each strategy. The results show that the distance-based and time-based strategies tend to have the lowest average waiting time for a long duration, whereas the distance-based and all utility-based strategies have the lowest average waiting time for a short duration. This indicates that the distance-based strategy is the optimal solution for minimising the average waiting time for this scenario. As for the number of decision changes, there are no significant differences between the strategies.

Figure 14e and f demonstrate the impact of different strategies on client satisfaction levels. As stated earlier, the ratio of disappointed clients to satisfied clients increases with an increase in α. For a long duration, the difference between the strategies in terms of the percentage of satisfaction at an excellent level is not substantial but the distance-based strategy clearly results in the lowest percentage of disappointment. Also, distance-based and utility-based strategies achieved the highest percentage of satisfaction at an excellent level and the lowest percentage of disappointment for a short duration.

Overall, under limited battery capacity, the distance-based strategy is most strongly associated with servicing more orders, generating more profit, lowering clients' waiting time, producing a high percentage of satisfaction at an excellent level and a low percentage of disappointment compared to the other strategies. The value-based strategy however is most strongly associated with generating more profit and increasing clients' waiting time. More interestingly, as α increases for a short service duration, the value-based strategy appears to be the optimal choice for profit maximisation.

6 Conclusion

Drones offer a range of various services that were difficult or impossible in the past, due to their size, speed and flexibility. This has stimulated the significant interest of many industries to create new business opportunities or to improve existing ones. However, there are a number of challenges to be overcome before drone services can be adopted in business scenarios. This paper explores a single drone-decision system using stereotypical distributions to cover a wide range of scenarios. Considering some possible drone strategies and the identified common factors that may affect the decision-making process, we conducted comprehensive simulation experiments to compare different strategies in terms of the length of service duration, mode of commitment, drone speed, the number of utility factors, clients' distribution, battery consumption and recharging. The following observations were noted.

- The length of service duration has a direct impact on the total generated profit and the number of serviced orders. It is better for the service provider to service long service duration orders rather than short service duration orders to maximise profit. On the other hand, servicing short service duration orders results in maximising the number of serviced orders.
- The adaptive and committed scenarios do not vary except with an increase in the request rate. For the distance-based strategy, the adaptive scenario was found to be generally better in all scenarios, whereas the committed scenario was better for the utility-based strategy.
- Flying at a higher speed was found to be generally better in all scenarios. However, the impact of a higher speed on the proposed strategies is uncertain. For example, when increasing the speed, the most influential strategy is the value-based strategy.
- Using two factors (distance and value) to build the utility function was found to be better than adding time in relation to these factors, due to the fact that being fair (time-based, or first-come-first-serve) did not improve the performance of the utility strategy. It seems that the first-come-first-serve strategy caused the drone to use inefficient routes (and perhaps ignore on-route servicing opportunities) if it has to service clients based on a strict time-based ordering.
- The client distribution does not matter significantly in terms of the choice of strategy. With low-frequency requests, all strategies have similar outcomes. However, an increase in the request rate results in a slight negative change with the random distribution. Despite the fact that using different distributions may affect the overall performance, all the scattered distributions have a quite similar impact with respect to their distance from the station.
- The strategies' performances were affected by the battery constraints.
- On average, the experiments show that the distance-based strategy is the optimal choice regarding increasing the number of serviced orders and profit, reducing waiting time and producing an excellent level of satisfaction and less disappointment.
- Overall, there are clear trade-offs between maximising revenue and maximising client satisfaction.

Previously, we looked at coordinating the flight paths of multiple drones [3], but this paper focuses in depth on single drone service systems. In particular, the paper discussed strategies that could help in designing a reliable drone service management system. As with all strategies, there are levels of uncertainty with respect to the type of service that future drone technology could provide. Future work will involve identifying the levels of uncertainty related to each strategy and exploring more strategies with multiple drones. Machine learning (ML) techniques can be used to learn request patterns from history, while in our simulations, we attempted the difficult problem of servicing requests generated at random by clients; and as they are difficult to anticipate, in actual life, there are likely patterns that will emerge which can be exploited via ML. Also, we will consider other factors (e.g. winds and wind speed, changes in air pressure, occurrence of storms and no-fly zones) that may affect on-drone decision-making processes to increase reliability, efficiency and profitability.

References

1. Alwateer M, Loke SW (2019) Decision-making for drone services in urban environments: a simulated study on clients' satisfaction and profit maximisation. In: The 16th IEEE Int'l conference on ubiquitous intelligence and computing (UIC),(accepted). IEEE
2. Alwateer M, Loke SW (2019) On-drone decision making for service delivery: concept and simulation. In: 2019 IEEE International conference on pervasive computing and communications workshops (UNAGI). IEEE, pp. 937–942
3. Alwateer M, Loke SW, Fernando N (2019) Enabling drone services: drone crowdsourcing and drone scripting. IEEE Access 7:110035–110049
4. Alwateer M, Loke SW, Rahayu W (2018) Drone services: An investigation via prototyping and simulation. In: Internet of Things (WF-IoT), 2018 IEEE 4th World forum on. IEEE, pp 367–370
5. Alwateer M, Loke SW, Zuchowicz AM (2019) Drone services: issues in drones for location-based services from human-drone interaction to information processing. J Locat Based Serv 1–34
6. Areias B, Humberto N, Guardalben L, Fernandes JM, Sargento S (2018) Towards an automated flying drones platform. In: VEHITS. pp 529–536
7. Bacco M, Berton A, Ferro E, Gennaro C, Gotta A, Matteoli S, Paonessa F, Ruggeri M, Virone G, Zanella A (2018) Smart farming: opportunities, challenges and technology enablers. In: IoT vertical and topical summit on agriculture-tuscany (IOT Tuscany), 2018. IEEE, pp 1–6
8. Bielen F, Demoulin N (2007) Waiting time influence on the satisfaction-loyalty relationship in services. Manag Serv Qual 17(2):174–193
9. Bogdan P, Pedram M (2018) Toward enabling automated cognition and decision-making in complex cyber-physical systems. In: Circuits and systems (ISCAS), 2018 IEEE International symposium on. IEEE, pp 1–4
10. Brooker P (2008) Sesar and nextgen: investing in new paradigms. J Navig 61(2):195–208
11. Chen Y, Hu H (2013) Internet of intelligent things and robot as a service. Simul Model Pract Theory 34:159–171
12. Claesson A, Svensson L, Nordberg P, Ringh M, Rosenqvist M, Djarv T, Samuelsson J, Hernborg O, Dahlbom P, Jansson A et al (2017) Drones may be used to save lives in out of hospital cardiac arrest due to drowning. Resuscitation 114:152–156
13. Daftry S, Hoppe C, Bischof H (2015) Building with drones: accurate 3d facade reconstruction using mavs. In: Robotics and automation (ICRA), 2015 IEEE International conference on. IEEE, pp 3487–3494
14. Di Franco C, Buttazzo G (2015) Energy-aware coverage path planning of uavs. In: 2015 IEEE International conference on autonomous robot systems and competitions. IEEE, pp 111–117
15. Doole M, Ellerbroek J, Hoekstra J (2018) Drone delivery: urban airspace traffic density estimation. In: Eight SESAR innovation days conference
16. Juan Jesús Roldán Pablo Garcia-Aunon EPT, Barrientos A (2019) Swarmcity project: Can an aerial swarm monitor traffic in a smart city? In: 2019 IEEE International conference on pervasive computing and communications workshops (UNAGI). IEEE, pp 862–867
17. Lin Q, Wang X, Wang Y (2018) Cooperative formation and obstacle avoidance algorithm for multi-uav system in 3d environment. In: 2018 37th Chinese control conference (CCC). IEEE, pp 6943–6948
18. Loke SW (2016) Smart environments as places serviced by k-drone systems. J Ambient Intell Smart Environ 8(5):551–563
19. Loke SW, Alwateer M, Abeysinghe Achchige Don VS (2016) Virtual space boxes and drone-as-reference-station localisation for drone services: An approach based on signal strengths. In: Proceedings of the 2nd Workshop on micro aerial vehicle networks, systems, and applications for civilian use. ACM, pp 45–48
20. Natalizio E, Surace R, Loscri V, Guerriero F, Melodia T (2012) Filming sport events with mobile camera drones: Mathematical modeling and algorithms. https://hal.inria.fr/hal-00801126. [Online; posted Dec-2012]
21. Sabo C, Cohen K (2013) Experimental validation of the allocation of uavs under communication restrictions. In: 51st AIAA Aerospace sciences meeting including the new horizons forum and aerospace exposition. p 1036
22. Shukla A, Xiaoqian H, Karki H (2016) Autonomous tracking and navigation controller for an unmanned aerial vehicle based on visual data for inspection of oil and gas pipelines. In: Control, automation and systems (ICCAS), 2016 16th International conference on. IEEE, pp 194–200
23. Sunil E, Hoekstra J, Ellerbroek J, Bussink F, Nieuwenhuisen D, Vidosavljevic A, Kern S (2015) Metropolis: Relating airspace structure and capacity for extreme traffic densities. In: ATM seminar 2015, 11th USA/EUROPE Air traffic management R&D seminar
24. Tang L, Shao G (2015) Drone remote sensing for forestry research and practices. J For Res 26(4):791–797
25. Thiels CA, Aho JM, Zietlow SP, Jenkins DH (2015) Use of unmanned aerial vehicles for medical product transport. Air Med J 34(2):104–108
26. Yapp J, Seker R, Babiceanu R (2016) Uav as a service: A network simulation environment to identify performance and security issues for commercial uavs in a coordinated, cooperative environment. In: International workshop on modelling and simulation for autonomous systems. Springer, pp 347–355
27. Zermani S, Dezan C, Euler R (2017) Embedded decision making for uav missions. In: Embedded computing (MECO), 2017 6th Mediterranean conference on. IEEE, pp 1–4
28. Zhang YH, Shi F, Ruan X, Yang YJ, Jiang Z (2018) Uav autonomous charging system based on multi-information cooperative positioning. In: 2018 7th International conference on energy, environment and sustainable development (ICEESD 2018). Atlantis Press
29. Zhao F, Zeng Y, Wang G, Bai J, Xu B (2018) A brain-inspired decision making model based on top-down biasing of prefrontal cortex to basal ganglia and its application in autonomous uav explorations. Cogn Comput 10(2):296–306