Revenue-Driven Scheduling in Drone Delivery Networks with Time-sensitive Service Level Agreements

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ABSTRACT

Drones are widely anticipated to be used for commercial service deliveries, with potential to contribute to economic growth, estimated at £42 billion in the UK alone by the year 2030. Alongside air traffic control algorithms, drone-based courier services will have to make intelligent decisions about how to deploy their limited resources in order to increase profits. This paper presents a new scheduling algorithm for optimising the revenue of a drone courier service provider in time-sensitive environments. The inputs to the algorithm are a monotonically decreasing value over time function which describes the service level agreement between the service provider and its customers. The second is the anticipated drone flight-time duration distribution. Our results show that the newly developed scheduling algorithm, Least Lost Value, inspired by concepts for real-time computational workload processing, is able to successfully route drones to extract increased revenue to the service provider than two widely-used scheduling algorithms: First Come First Served and Shortest Job First, in terms of realised revenue.

CCS CONCEPTS

• **General and reference → Performance**; • **Software and its engineering → Scheduling**;

KEYWORDS

Drone, Data Analytics, Intelligent Scheduling, Time Value Functions

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1 INTRODUCTION

The demand for prompt courier service continues to grow especially in industries where timely delivery of parcels is paramount [1, 19, 20, 30]. Conventional vehicles have dominated the courier service delivery for some time. Despite their success, the lack of speed continues to limit the effectiveness of conventional vehicles in providing prompt courier service delivery [20]. Increasingly, congested road networks – and in some cases challenging terrain which inhibits the use of roads – has meant the problem continues unabated. This problem is expected to only grow bigger with global e-commerce sales projected to reach US$4.5 trillion in 2021, fueling the need for timely deliveries [30]. The advent of drones offering a faster mode of transportation is poised to revolutionise the courier services business [30]. If properly routed, drones have the potential to provide better courier services which can benefit both the user and the service provider. The user benefits from prompt delivery while the service provider benefits from increased revenue resulting from better allocation of scarce resources. In the past, similar challenges have been faced in continuous real-time computational workload increases needing to meet time constraints, while resources remain limited [15]. Drawing inspiration from this previous work, the aim of this research is to present a novel optimisation algorithm for the routing of drones in the context of time-sensitive services, and to test its effectiveness in enhancing revenue to the service provider. The contributions of this paper are:

(1) We propose the notion of Time Value of Service Delivery, which defines *"value"* as a monotonically decreasing function of time that captures the service level agreement between a courier service provider and its customer.
(2) We present a new scheduling algorithm, Least Lost Value (LLV), that uses the Time Value of Service Delivery function to drive a revenue-driven scheduling model for time-sensitive courier service deliveries
(3) We demonstrate the effectiveness of the LLV algorithm in a drone delivery network that can outperform two widely-used scheduling algorithms, First Come First Served (FCFS) [24] and Shortest Job First (SJF) [10], in enhancing revenue to the service provider.

The paper is organised as follows. Section 2 discusses the growth of e-commerce and how drone technology is viewed as the future for commercial service deliveries requiring intelligent scheduling. We examine related work and propose a new notion, the Time Value of Service Delivery function, that can be used to route drones in time-sensitive delivery networks. Section 3 presents a newly developed scheduling algorithm, Least Lost Value (LLV), that uses the Time Value of Service Delivery function, for revenue-driven scheduling. Section 4 discusses the drone-delivery network simulation, developed for the study, to test the effectiveness of LLV in routing drones deliveries. Section 5 presents the experiment results which show the LLV algorithm outperforming widely-used scheduling algorithms in extracting increased revenue to the drone service provider. Concluding remarks are given in Section 6.

2 BACKGROUND

Drone is a common term to describe an unmanned aerial vehicle (UAV), with a ground-based controller and a system of communication between the controller and the drone. Various versions of the drone have been around since the first world war, originally developed as part of air-defense strategies [20]. However, more recently, drone technology is being seen as disruptive technology by organisations faced with increasing pressures for faster and efficient deliveries in an environment of limited resources and reduced earnings [12, 20, 29]. Current surveys project drone technology as poised to contribute to cost-savings, increased productivity/efficiency and job creation in various industries [19]. In the UK alone, the expected GDP uplift is over £40bn across all sectors impacted by drone technology [8].

One particular sector that has seen increased investments using this technology is in drone delivery networks. In the Americas region, the pattern is similar with an unprecedented increase in revenue from $40 million in 2012 to $1 billion in 2017 in the drone-delivery industry [25]. While security concerns by governments, continue to impose strict regulations, this has not stopped the interest and investment in drone delivery. Amazon with a US e-commerce market-share of 49.1% in online retail [23] is pioneering *Amazon Prime Air* [14] for its speed of delivery and what it brings with increased revenue (Value) obtained [27], seen in Figure 1.

While current use of drone delivery networks target niche use-cases (e.g. medical aid), there is an overall theme that recognises the importance of this new technology in time-sensitive environments [9]. The sooner the delivery, the more the benefit to the user [9]. Put differently, courier service providers are increasingly seeing the potential for increased revenue from faster delivery. Further, with 90% of online delivery parcels weighing under 5lbs, well suited for drone carrying capacity, it is rapidly becoming the vehicle of choice for "last-mile" logistics [20]. Therefore, it is predicted it will not be too long before drones are used in urban areas of high density, for commercial purposes [12, 19, 29]. In such an environment of increasing demand for drone delivery services, an intelligent scheduling mechanism for the routing of the delivery will be required by service providers, with the aim of enhancing revenue.

Figure 1: Amazon Delivery Drone - Prime Air [14]

This research draws its inspiration from a similar problem faced previously in real-time computational workload scheduling in finding a solution for intelligent scheduling. Programs that implement logically correct algorithms were deemed inaccurate, if timing requirements were not met [26]. In some quarters the failure to meet its required time constraint deadline, was as good as having failed to process the job altogether [4, 15, 26]. Jensen notes that the primary distinguishing feature of a real-time system is that response time is crucial and the completion of a process adds utility (benefit) that can be modelled as a function of time, i.e. utility varies with time [15]. This concept draws very close parallels to drone delivery networks where if critical delivery requests are identified correctly, they can be made in good time to provide benefit. Using a view of value over time function for the service delivery, requests that contribute higher value, given limited resources, can be routed first [1, 20]. Jensen's proposed time-driven scheduler using his Best Effort Value (BEValue) algorithm, bound on utility as a time function, was able to schedule real-time computational workload to successfully meet time constraints [15]. Given its success, further contributions to Jensen's algorithm have continued, listed in Table 1.

Table 1: Improvements in Real-Time Scheduling Algorithms using Utility Functions

Date	Algorithm	Improvement
1985	Best Effort Value 2 [15]	Support for overload conditions
1990	Dependent Activity Scheduling [6]	Considers inter-task dependencies alongside utility functions
1996	Best Effort [5]	Support for multivalence task utility functions
1999	Dynamic Value Density [2]	Reduced task deadline misses
2006	Generic Utility Scheduling [18]	Maximises total accrued utility to the system
2017	MK Model [17]	Commitment to complete m of k tasks

Our review of these algorithms found them unsuited for scheduling in drone delivery networks. Firstly, a real-time system operates on the basis that some tasks will deliberately get dropped favouring tasks that contribute higher total utility to the system [17]. Though common practice in real-time processing environments, it is not a viable approach for drone-delivery services, where reliability of service completion is important [1]. Secondly, the time utility functions for real-time processing is determined using historical task duration metrics alongside system architect's expertise. This is not practical in drone-delivery networks where the service level agreement is jointly agreed between the courier service provider and the customer, a combined perspective of "Value" [11]. Finally, drone delivery networks are exposed to obstacles (e.g. static objects, no-fly-zones) that make the duration of the delivery highly stochastic. Although the high variability of runtime for computational processing is well-known, real-time processing algorithms do not make any provisions for reflecting the stochastic nature of task duration within the scheduling algorithm's decision-making. This research contends that the task duration is a random variable with a duration distribution and needs to be considered in the decision-making for the routing of drones.

This research proposes the notion of Time Value of Service Delivery, inspired by Jensen's work in real-time processing of computational workload, as a monotonically decreasing function of time that represents the delivery service level agreement between the courier service provider and the customer. Figure 2 is a diagrammatic representation of an arbitrary Time Value of Service Delivery function. These functions can be continuous or discontinuous and represented by either a single polynomial function or a set of piece-wise polynomial functions for a defined temporal interval.

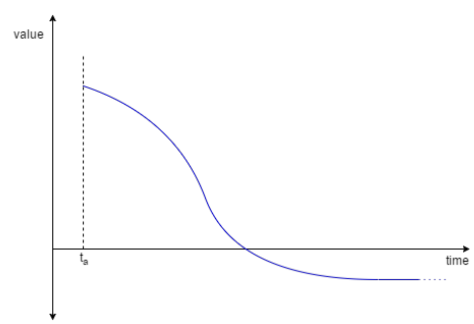

Figure 2: Time Value of Service Delivery Function

Further, this study suggests that the Time Value of Service Delivery function can be used to schedule deliveries in commercial drone delivery services to enhance revenue to the service provider. Under these time-sensitive circumstances, the routing of drones will work under two assumptions. The first is that the reward for processing a task monotonically decreases as a function of time, represented as the Time Value of Service Delivery. The second that the duration of the task is stochastic and can be represented as a distribution. While these quantities are quite hard to assess in the context of real-time computational processing environment, they are very naturally specified in the context of drone delivery networks. Firstly, in the case of the cost payoff function, in terms of the service level agreement between the provider of the delivery service and the customer. Secondly, the estimation of the distribution of the task duration is also much easier as the drone's capabilities are known, i.e. the weight of the parcel and its location destination is known.

3 REVENUE-DRIVEN SCHEDULING ALGORITHM

This section discusses the newly developed algorithm that uses the Time Value of Service Delivery function to enhance revenue to the service provider. The first step in deriving the scheduling algorithm was to determine the scheduling objective. Given our overriding goal to enhance revenue to the service provider, this research proposes that the scheduling objective is to prioritise the tasks that increases revenue to the service provider.

Secondly, the decisions around which attributes would be used in the algorithm was driven from the two assumptions highlighted in previous Section 2. While traditional scheduling algorithms tend to assume a fixed duration for the tasks, the duration for service deliveries are instead largely stochastic and needs to be represented as a task duration distribution. Further, contrary to the assumption of a fixed deadline when tasks need to be completed, this research assumes the problem as being more complex. We argue that the intrinsic *"value"* of the service delivery to both the customer and the courier service provider around the deadline can be represented as a Time Value of Service Delivery function as seen in Figure 2. Therefore, we conclude that the attributes relevant for a revenue-driven scheduling algorithm for courier service deliveries are: (1) the Time Value of Service Delivery function (2) the service delivery task duration distribution.

3.1 Least Lost Value Algorithm (LLV)

The development of LLV is grounded on the idea that the sooner a service delivery (job) is made the better, given a monotonically decreasing Time Value of Service Delivery function. In developing LLV we faced a number of challenges regarding how best to incorporate attributes of interest into the algorithm. For example, we were aware LLV needed to consider that any job selected results in an opportunity cost for the jobs not selected. Further, it was vital to limit the complexity of the use of the attributes in the algorithm so as not to compromise its effectiveness [3]. Faced with such challenges, we adopted the Constrained Scheduling Problem (CSP) method to guide the development of LLV. CSP looks at each attribute as a constraint that needs to be satisfied, while trying to limit the complexity of the search, especially in a dynamic environment, where each attribute can take on multiple values [16]. Keng highlights that CSP, is more suited for environments where task duration and resources are fixed which contrasts the stochastic environment envisaged in this study. However, he argues the problem of diminishing resources in CSP can be adequately solved using the *cruciality* of the solution [16]. *Cruciality* measures how a solution impacts the tasks not selected and what he terms as the *least impact policy* [16]. Encouraged by Keng's findings, we argue that LLV should consider both the potential value gained and the potential value lost to produce a scheduling metric that will prioritise tasks with the least negative impact.

In this research we define the *Potential Gain Value* (PGV) as the value gained by the job selected for processing at current time, versus starting the job later, after another job completes. The *Potential Lost Value* (PLV) is defined as the value lost from all the jobs not selected for processing at current time, versus starting these jobs later, after the selected job has completed. A combination of PLV and PGV will yield a scheduling metric *Net Lost Value*. LLV will order jobs with the lowest *Net Lost Value* to produce a schedule that is aimed at extracting increased value (revenue) to the service provider. The intention is to decrease the net value lost (for the delivery requests not selected) while increasing the net value gained (for the selected delivery requests).

Formally, given a set of jobs J, the *Net Lost Value* (NLV) for selecting job j_i is defined as follows:

$$NLV(j_i) = PLV(j_i) - PGV(j_i) \tag{1}$$

As this scheduling algorithm will need to work in an environment where the task duration cannot be predicted in any amount of certainty, both PLV and PGV will use the Expected Value from the task duration distribution's probability density function and its associated cost payoff function, in its calculation. Therefore, the Expected Value (EV) for job j_i with the cost function V_i, current time t_c and a probability density function $f_i(t)$ of the task duration distribution, is defined as follows:

$$EV(j_i, t_c) = \int_{t_c}^{\infty} V_i(t).f_i(t - t_c)\, dt \tag{2}$$

The *Potential Lost Value* (PLV) of selecting job j_i is the sum of the lost value of all other remaining jobs (j_k) not selected for processing, defined as:

$$PLV(j_i) = \sum_{j_k \in J, k \neq i, k=1}^{n} \big(EV(j_k, t_c) - EV(j_k, t_c + p_i)\big) \tag{3}$$

where:
n: number of jobs in set of job J
t_c: current time
p_i: non-weighted expected value of the task duration distribution for job j_i given probability density function $f_i(t - t_c)$, defined as:

$$p_i = \int_{t_c}^{\infty} (t - t_c).f_i(t - t_c)\, dt \tag{4}$$

The *Potential Gain Value* (PGV) of selecting job j_i is the difference of value between processing job j_i at current time t_c versus at later time, $t_c + \overline{p_i}$, defined as

$$PGV(j_i) = (EV(j_i, t_c) - EV(j_i, t_c + \overline{p_i})) \tag{5}$$

where $\overline{p_i}$ is calculated using the non-weighted expected value of the task duration distribution of the jobs not selected k with probability density function $f_k(t - t_c)$, defined as:

$$\overline{p_i} = (\sum_{k \neq i, k=1}^{n} p_k)/(n-1) \tag{6}$$

and

$$p_k = \int_{t_c}^{\infty} (t - t_c).f_k(t - t_c)\, dt \tag{7}$$

One advantage of PLV is that in considering the value lost from the jobs not selected it inadvertently considers discontinuity of value in the Time Value of Service Delivery function, described in Figure 2 as well as any impending penalties. Therefore, jobs within the workload are likely to be scheduled for completion, before the critical value loss of discontinuities and penalties. The LLV scheduling is detailed as Algorithm 1, where the job workload is broken down into an array of individual job objects, *jobList*[1].

Algorithm 1 LLV Scheduling algorithm

```
procedure LLVjobSort(jobList, timePassed)
    jobSet ← jobList
    currentTime ← timePassed
    lost ← 0.0
    won ← 0.0
    i ← 1
    for job_i ∈ jobSet do
        lost = PLV(job_i, jobSet, currentTime)
        won = PGV(job_i, jobSet, currentTime)
        job_i.netLostValue = (lost − won)
        i = i++
    jobList ← sort jobs in jobSet by increasing netLostValue
    return jobList

                                    ▷ Potential Lost Value calculation
procedure PLV(job, jobSet, currentTime)
    lostValueJob ← 0.0
    j ← 1
    job.timeLeft = expectedValueDurationDistr(job)
    − getTimeProcessed(job)
    for job_j ∈ jobSet do
        if job_j ≠ job then
            lostValueJob = lostValueJob +
            expectedValue(job_j, currentTime) -
            expectedValue(job_j, currentTime +
            job.timeLeft)
        j = j++
    return lostValueJob

                                    ▷ Potential Gain Value calculation
procedure PGV(job, jobSet, currentTime)
    wonValueJob ← 0.0
    j ← 1
    expectedValueOnDuration ← MINVALUE
                ▷ MINVALUE is the smallest positive non-zero value of type double
    for job_j ∈ jobSet do
        if job_j ≠ job then
            expectedValueOnDuration =
            Math.max(expectedValueOnDuration,
            expectedValueBasedOnDuration(job_j))
        j = j++
    wonValueJob ← expectedValueOnDuration
    return wonValueJob
```

[1]Each job object in the joblist contains: (1)Job Id (2)Cost Payoff Function (3)Duration Distribution (4)Job Arrival Time

4 DRONE ROUTING USING REVENUE DRIVEN SCHEDULING

As discussed in Section 2, drone delivery networks are viewed as the solution for faster deliveries, given the projected growth in global e-commerce. Further, this research postulates that the expected surge in delivery volumes will outweigh available resources. Thus, the need for intelligent scheduling for the routing of drone deliveries, if service providers are to remain profitable. Hence, this study proposes a novel algorithm LLV, presented in section 3, that can schedule drone deliveries with the aim of enhancing revenue to the service provider. LLV uses the Time Value of Service Delivery function, discussed in Section 2 to represent the service level agreement between the drone service provider and the customer. This section describes the drone-delivery network simulation[2] that was developed in this study to test the effectiveness of LLV in routing drones with the aim of enhancing revenue to the service provider. It also includes a discussion on how a service level agreement between the courier service provider and the customer was modeled as a cost payoff function to be used by LLV for revenue-driven scheduling.

4.1 Drone Delivery Architecture

In developing the drone delivery network simulation, four considerations were made to reflect real-life features. First, with the advent of drone technology improvements, drones are now fully capable of avoiding physical obstacles and navigating to GPS locations on their own [7], thus will not need a persistent controller for governing its every movement. Second, if drone technology is to be used effectively for high-volume deliveries in urban areas, an autonomous aviation model will need to be implemented, between an unmanned central controller and its drones. Third, the drone delivery route will need to consider *No Fly Zone* (NFZ) restrictions, imposed by most city authorities. Finally, in the absence of customers providing delivery requests, the system will need to generate delivery orders as part of the simulation.

SpatialOS, a cloud-based distributed platform, was used for the development of the drone delivery network simulation [22]. We selected SpatialOS primarily as it adopts an *Entity-Component-Worker* model [21], which means each *Entity* consists of *Components* that define state and how other entities interact with them. This model provided the flexibility required for ease of scaling up the simulation to include larger number of entities and more complex components.

The drone delivery network simulation was run in its entirety as a cloud-based system, with the live state of the running simulation visualised using SpatialOS' built-in *Inspector* tool. Unity [28] was used to provide an initial snapshot[3] for the *simulation*. Using Unity, the objects – Controller, Drone, No-Fly-Zones – are used to populate the snapshot generated of the drone delivery network for the simulation. This snapshot can be edited with ease for future delivery network modifications. Figure 3 shows the user interface

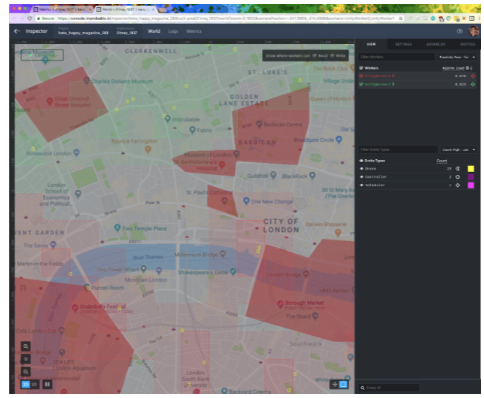

Figure 3: Drone Delivery Network Simulation (SpatialOS)

of the *Inspector* tool for visualising the simulated drone delivery network.

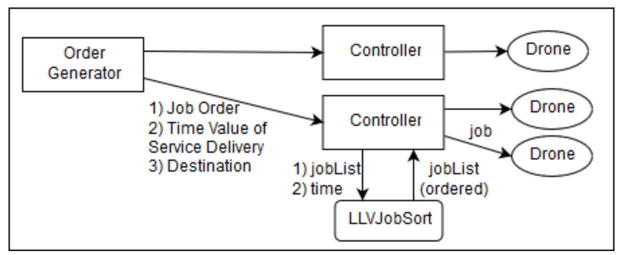

Figure 4: Drone Delivery Network using LLV

The *Entity(s)* in the simulation were: (1) Controller (2) Drone, (3) Order Generator. A single *Order Generator* generates customer's requests, a random destination coordinate of the "world" and a Time Value of Service Delivery function[4]. The virtual "world", is divided into smaller voronoi areas, each governed by a single *Controller* with n drones to perform the delivery. The *Order Generator* sends the job order request to the designated *Controller*. As discussed in Section 2, a delivery request's duration distribution can be easily determined using the known delivery destination, speed of the drone and historical duration of deliveries. The *Controller* invokes the LLV algorithm to prioritise the delivery request using the *jobList* object comprised of job details, cost payoff function and internally generated task duration distribution. The request with the lowest *Net Lost Value* is scheduled for the next available drone. Given the simulated drone delivery network is autonomous, the *Controller* is responsible for generating a list of NFZ-avoiding "waypoints" that a particular drone will follow to move from start to destination. The *Drone* will make a series of requests to the *Controller* for its next "waypoint" on reaching its previously provided "waypoint", until it reaches its destination. This simulation is a non-preemptive model. Figure 4 provides an illustration of this model.

[2]A simulation was used given regulation limitation and cost constraints in using real-life drones

[3]A snapshot represents the state of a simulated world at a point in time, storing each entity and the properties of its components

[4]The service level agreement for drone deliveries is discussed in Section 4.2

4.2 Drone Delivery Service Level Agreement

Traditional courier service level agreements are usually a set of fixed payment options for the customer to select from where the service provider guarantees delivery within a specified period of time, for a fee. Figure 5 is an example of a delivery service payment package model adapted from Amazon [13]. In contrast, high-volume drone delivery networks that are time-sensitive need to make intelligent scheduling decisions with no guarantees of the delivery, given limited resources. In this environment, courier service providers need to provide customers with a flexible payment structure that accounts for possible delivery delays. Therefore this study proposes the use of the traditional fixed payment model (Figure 5) alongside the new Time Value of Service Delivery function that combine to represent the time-sensitive service level agreement between the drone service provider and the customer. This research proposes that the Time Value of Service Delivery is a fixed percentage price reduction for every interval of t time delay.

Package Type	Weight (g)	Delivery Fee (£)			
		Standard	Priority	Urgent	Super Priority
Small Letter	0 - 100	0.60	0.90	1.35	2.03
Large Letter	0 - 250	0.80	1.20	1.80	2.70
Small Envelope	0 - 100	1.09	1.64	2.45	3.68
Standard Envelope	0 - 100	1.21	1.82	2.72	4.08
	101 - 250	1.34	2.01	3.02	4.52
	251- 500	1.54	2.31	3.47	5.20
Large Envelope	0 -1000	1.77	2.66	3.98	5.97
Parcel	0 - 250	1.73	2.60	3.89	5.84
	251 - 500	1.79	2.69	4.03	6.04
	501 - 1000	1.84	2.76	4.14	6.21
	1001 - 1500	2.26	3.39	5.09	7.63
	1501 - 2000	2.48	3.72	5.58	8.37
	2001 - 3000	3.32	4.98	7.47	11.21

Figure 5: Drone Delivery Payment Structure

In this experiment, we implemented two possible options for the Time Value of Service Delivery functions. Figure 6 reflects a "step-wise" price reduction of equal proportions while Figure 7 represents a "halving" of the price. We believe that this service level agreement model provides the flexibility, in the future, to adapt to a more varied view of the time-sensitive diminishing "value" for the drone delivery. This can be achieved through increasing the available options for the Time Value of Service Delivery functions.

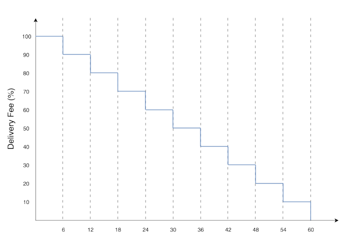

Figure 6: Time Value of Service Delivery (Step-wise)

In the drone delivery network simulation, the *Order Generator* randomly selects a delivery fee from the Payment Package in Figure 5 using Algorithm 2 as well as selects one of the two available

Figure 7: Time Value of Service Delivery (Halving)

options of Time Value of Service Delivery functions. This information is passed from the *Order Generator* to the *Controller* for each delivery request. The *Controller* using a combination of the Time Value of Service Delivery function and Payment Package deduces a cost payoff function [5]. The *Controller* invokes the *LLVjobSort* detailed in Algorithm 1, to sort the delivery requests, scheduling the request with the lowest *Net Lost Value* to enhance the value (revenue) obtained by the service provider.

Algorithm 2 Payment Package Selection

```
procedure SELECTPAYMENTPACKAGE(requestID)
    requestId ← requestID
    pktType ← random select Package Type
    weight ← random(pktType)
    priority ← random select priority
    deliveryFee = getDeliveryFee(pktType, weight, priority)
    return requestID, deliveryFee
```

4.3 Drone Delivery Experiment Simulation

The selected area for the drone delivery network simulation was a location in Central London covering an area of 5km x 4km with a routable boundary of 4.8km x 3.8km, allowing a 100m border to avoid simulating entities on the 'world" boundary. The *world* was divided into two sections with 5 NFZ, one *Controller* per section, servicing 15 *Drones*. Figure 8 provides an illustration of the initial snapshot of the *world* used in this experiment.

A time-sensitive environment was achieved through an *Order Generator* that recreated customers placing delivery requests of high volume and stochastic arrival times, on average one every 30s, with randomly generated delivery destinations, within the *world*. Additionally, each order was randomly assigned one of two Time Value of Service Delivery functions, illustrated in Figure 6 and Figure 7.

The simulation was run for a period of 6 hours to test the capability of the LLV algorithm in scheduling the routing of drone deliveries to enhance the revenue of the service provider. Additionally, two popular scheduling algorithms used in traditional package deliveries, First Come First Served (FCFS) [24] and Shortest Job

[5] As example, a payment structure of Figure 5 combined with Time Value of Service Delivery function of Figure 6, that takes 5 minutes to deliver a "Standard Envelope" weighing 500g of "Delivery Type" *Super Priority* will obtain the full "Value" of £5.20. If the delivery takes 19 minutes, a reduced "Value" of £3.64 is obtained, and further delay in delivery time of 55 minutes will see a considerable reduction of "Value" to £0.52.

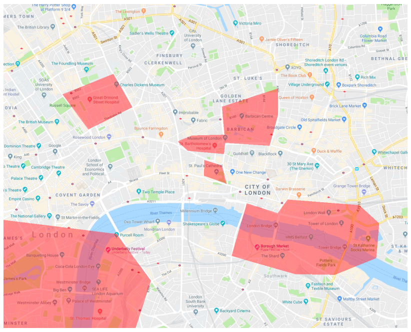

Figure 8: Drone Delivery World with NFZ

First (SJF) [10], was run in parallel for the purposes of comparison with LLV. A queue size of 40 was used in the experiment. The FCFS implementation discarded delivery requests received once the queue was full. For SJF the queue was sorted when a new delivery request was received, requests with the shortest duration first. The LLV implementation reordered the queue, when a drone became available for delivery, allowing the queue to grow beyond the size of 40. Some assumptions were made in this experiment:

(1) Each *Drone* travels at a constant speed for the delivery
(2) The service provider maintains a one hour service level agreement, with a fixed penalty of £5 paid out to the customer after this period
(3) The simulation assumes the drone delivery network targets "last-mile" logistics, discussed in Section 2 and that the package deliveries can be brought to the central controller

5 DRONE DELIVERY - EXPERIMENTAL RESULTS AND DISCUSSION

This section discusses the results[6] of the experiment obtained from running a simulation of a drone delivery network using three scheduling algorithms in parallel to route the drones: (1) LLV (2) FCFS (3) SJF. The total "value" (revenue) obtained was compared and contrasted between LLV and traditional scheduling algorithms: FCFS and SJF.

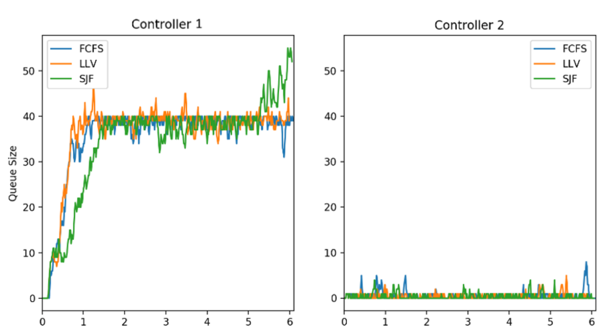

Figure 9: Queue Size over Time

[6]Detail results location: https://www.doc.ic.ac.uk/~ss11715/DroneSimulationResults/

Figure 9 shows that the queue size load of requests was higher in *Controller 1* than in *Controller 2*. The overload of requests in *Controller 1* meant that the algorithms were used more frequently to make scheduling decisions for drone deliveries than in *Controller 2*.

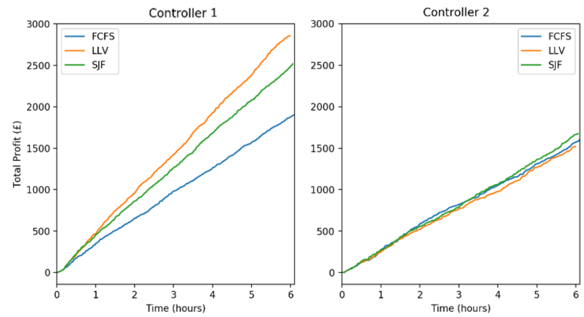

Figure 10: Total Revenue over Time

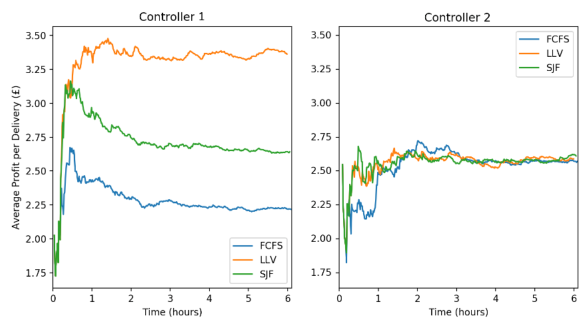

Figure 11: Average Revenue Per Drone Delivery

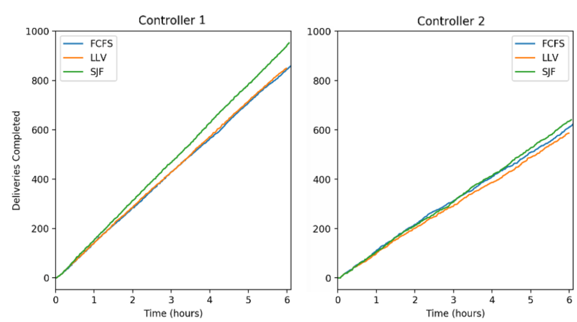

Figure 12: Completed Deliveries over Time

The experiment results in Figure 10 show that when the system was under overload (*Controller 1*), LLV was able to deliver 48% and 31% of increased revenue to the service provider than FCFS and SJF. On average LLV extracted £1.15 more revenue per delivery request than FCFS and £0.80 than SJF, illustrated in Figure 11. Interestingly, the enhanced revenue extracted by LLV was not derived from increased deliveries. Total deliveries completed by LLV, FCFS and SJF were 850, 859 and 983 respectively as shown in Figure 12.

These results indicate that the LLV scheduling decision based on a consideration of the Time Value of Service Delivery was able to successfully drive scheduling in a time-sensitive environment to extract increased revenue to the service provider. Additionally, LLV achieved this from a reduced number of deliveries than FCFS and SJF which suggests a more efficient scheduling model.

Where there was no overload in the drone delivery network (*Controller 2*), LLV did not perform as well as FCFS and SJF. LLV extracted 6% and 10% less total revenue than FCFS and SJF. This was expected as no overload meant that no scheduling decisions were required. SJF working through the deliveries of closer destinations would complete more delivery requests, such obtaining increased value (i.e. revenue). LLV would behave similar to FCFS scheduling the deliveries as they arrive. However, we did expect LLV to extract less total revenue than FCFS given the delays in generating the cost payoff function, that was not required given deliveries were less than available drones.

These results show that the notion of Time Value of Service Delivery, introduced in Section 2, is capable of driving scheduling decisions in a time-sensitive environment. The experiment illustrates the practicality of how a service level agreement between the customer and a service provider can be represented as a cost payoff function and integrated into a revenue-driven scheduling model. Finally, these results confirm that the novel LLV algorithm has been able to schedule deliveries in a time-sensitive drone-delivery network simulation to enhance revenue to the service provider, more effectively than widely-used FCFS and SJF scheduling algorithms.

6 CONCLUSION AND FUTURE WORK

Delivery providers are increasingly looking to the skies for solutions to challenges facing light weight package deliveries by embracing drone technology. With demand for timely deliveries increasing exponentially from e-commerce, while conventional delivery vehicles remain limited, highly utilised and subject to challenging terrains and urban congestion, service providers are increasingly convinced that drones is the much needed solution. Within this context, this paper proposes the notion of Time Value of Service Delivery as a monotonically decreasing function of time and presents a new intelligent scheduling algorithm that uses it. Specifically, we have developed a revenue-driven scheduling algorithm, Least Lost Value (LLV), which supports idiosyncrasies such as stochastic task duration and time-sensitive environments, with aim to enhancing revenue to courier service providers. LLV was used in a drone delivery network simulation to route drones using a revenue-driven scheduling model. Our results show that the LLV scheduling algorithm is able to extract increased revenue to service providers compared to traditional scheduling algorithms, 48% and 31% more revenue than FCFS and SJF respectively.

One avenue for future work would be to test the effectiveness of the LLV algorithm in driving intelligent scheduling for big data environments. Big data suffers from a deluge of data needing some form of intelligent scheduling for timely processing of data for improved decision-making. LLV could be useful in driving the scheduling needs, especially that consumers of the processed data may have varying views of its "value" that diminishes with time.

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