# 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 these highly utilised time-sensitive service delivery systems. The first input to the algorithm is 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 in comparison with 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, dominated by conventional vehicles, continues to grow especially where timely delivery is paramount [1, 17, 18, 24]. Despite their success, lack of speed continues to limit service delivery effectiveness [18]. Increasingly congested road networks and challenging terrain has meant the problem continues unabated. This problem is growing bigger with global e-commerce sales projected to reach US$4.5 trillion in 2021, fueling the need for timely deliveries [24]. Recently, drone technology is being explored by organisations faced with increasing pressures for faster and efficient deliveries in an environment of limited resources and reduced earnings [12, 18, 23].

Drones, i.e. unmanned aerial vehicles (UAVs) with a ground-based controller, are poised to contribute over £40bn to the UK economy in terms of cost-savings, increased productivity/efficiency and job creation [9, 17]. It is predicted it will not be too long before they are used in urban areas of high density, for a variety of commercial purposes [12, 17, 23]. Indeed, with 90% of online delivery parcels weighing under 5lbs, drones are rapidly becoming the vehicle of choice for "last-mile" logistics [18]. Amazon with a US e-commerce market-share of 49.1% in online retail [21], is pioneering *Amazon Prime Air* [4] for its speed of delivery and what it brings with increased revenue (value) obtained [22].

Drones are set to revolutionise the courier services business [24]. In such an environment of increasing demand and scarce resources, an intelligent scheduling mechanism for drone delivery routing will be required by service providers. The aim of the present research is to present a novel optimisation algorithm for the routing of drones in time-sensitive service delivery systems, and to test its effectiveness in enhancing the revenue of the service provider. The contributions of this paper are:

(1) We propose the notion of Time Value of Service Delivery, which defines a *"value"* function as a Service Level Agreement between a service provider and its customer.
(2) We present a new algorithm, Least Lost Value (LLV), that uses the Time Value of Service Delivery function to aid revenue-driven scheduling in time-sensitive courier service systems.
(3) We developed a cloud-based drone delivery simulation to schedule deliveries with stochastic service duration times.
(4) We demonstrate LLV's effectiveness in a drone delivery network that can outperform two widely-used scheduling algorithms, Shortest Job First (SJF) [10] and First Come First Served (FCFS) in enhancing revenue to the service provider.

# 2 REVENUE-DRIVEN SCHEDULING ALGORITHM

## 2.1 Time Value of Service Delivery Function

In time-sensitive service delivery systems, critical deliveries made in good time can increase value of the service encounter [1, 18]. This research proposes the notion of Time Value of Service Delivery as a monotonically decreasing function of time that describes the payoff of a Service Level Agreement mutually agreed between a service provider and a customer. 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. Although, this concept draws close parallels to real-time utility functions [2, 6, 7, 15, 16], they differ. Firstly, the agreement between the service provider and the customer is a combined perspective of "Value" [11] where time utility functions are determined by system architect's expertise [13]. Secondly, real-time utility functions adopts a fixed deadline when utility is zero, while this research assumes a more complex problem where service duration is a random variable with a duration distribution. In the context of these time-sensitive drone delivery networks, non-deterministic events are the cause for stochastic service duration times (e.g. weather conditions, other air traffic). This research proposes using the Time Value of Service Delivery function to schedule time-sensitive service deliveries with stochastic service duration times to enhance revenue to the service provider.

## 2.2 Least Lost Value Algorithm (LLV)

The development of the new scheduling algorithm for time-sensitive service delivery systems, 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 alongside stochastic service duration times. That is, the attributes relevant for a time-sensitive revenue-driven scheduling algorithm are: (1) the Time Value of Service Delivery function (2) the service delivery task duration distribution.

The challenge in developing LLV was to limit the complexity of the use of the attributes in the algorithm so as not to compromise its effectiveness [5], while considering that any job selected results in an opportunity cost for the jobs not selected. Faced with this challenge, we adopted the Constrained Scheduling Problem (CSP) method to guide the development of LLV. CSP aims to satisfy each constraint (attribute), while trying to limit the complexity of the search [14]. Keng acknowledges CSP is not suited for stochastic environments, envisaged in this study. However, he argues *crucial-ity* can adequately solve dynamic constraints, in what he terms as the *least impact policy* [14]. 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. Therefore, LLV is expressed in terms of two metrics: *Potential Gain Value* (PGV) – the value gained by the job selected for processing at current time, versus starting the job later, after another job completes – and *Potential Lost Value* (PLV) – 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.

Subtraction of PGV from PLV yields the scheduling metric *Net Lost Value*. LLV will order jobs by increasing *Net Lost Value* (revenue). This approach inadvertently also considers discontinuity of value in the Time Value of Service Delivery function as well as any impending penalties. Formally, given a set of jobs $J$, the *Net Lost Value* (NLV) for selecting job $j_i$ at time $t_c$ is defined as follows:

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

As the task duration is stochastic, both PLV and PGV use the Expected Value derived from the task duration distribution input. The Expected Value ($EV$) for job $j_i$ with the cost function $V_i$, start time $t_c$ and a probability density function $f_i(t)$ of the task duration, 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:

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

where $n$ is the number of jobs in set of job $J$, current time, $t_c$ and $ED(j_i)$ the expected value of the task duration for job $j_i$, defined as:

$$ED(j_i) = \int_{0}^{\infty} t f_i(t)\, dt \tag{4}$$

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, $t_c + \overline{ED}(j_i, J)$, defined as

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

where $\overline{ED}(j_i, J)$ is calculated using the average of the sum of the expected values of the task duration each job not selected:

$$\overline{ED}(j_i, J) = (\sum_{k \neq i, k=1}^{n} ED(j_k))/(n-1) \tag{6}$$

LLV is summarised in Algorithm 1.

**Algorithm 1** LLV Scheduling algorithm

**procedure** LLVJOBSORT($J$, $t_c$)
  **for** $job \in J$ **do**
    $job.NLV = PLV(job, J, t_c) - PGV(job, J, t_c)$
  *sort jobs in J by increasing NLV*
  **return** $J$
**procedure** PLV($job$, $J$, $t_c$)
  $lostValue \leftarrow 0$
  **for** $job' \in J$ **do**
    **if** $job' \neq job$ **then**
      $lostValue += EV(job', t_c) - EV(job', t_c + ED(job))$
  **return** $lostValue$
**procedure** PGV($job$, $J$, $tc$)
  $wonValue = EV(job, t_c) - EV(job, t_c + \overline{ED}(job, J))$
  **return** $wonValue$

# 3 DRONE ROUTING USING REVENUE DRIVEN SCHEDULING

A drone delivery network simulation[1] was developed to test the effectiveness of LLV in a time-sensitive service delivery system. The architecture and experimental results are presented in this section.

## 3.1 Drone Delivery Simulation Architecture

The architecture makes four considerations to reflect real-life features in the drone delivery simulation: (1) drones need only a simple Controller that gives routes as a series of waypoints [8], (2) an autonomous aviation model is required to support high-volume deliveries, expected in urban areas (3) drone delivery route will need to consider *No Fly Zone* (NFZ) restrictions, imposed by most city authorities and (4) delivery order generation is required as part of the simulation.

SpatialOS, a cloud-based distributed platform, was used to develop the drone delivery network simulation [20]. The selection was primarily for scalability of its *Entity-Component-Worker* model [19] and visualisation capability using its *Inspector* tool. The *Entity(s)* in the simulation were: (1) Controller (2) Drone, (3) Order Generator.

The drone delivery network simulation covered a 5km × 4km area of Central London, selected given researcher familiarity and availability of NFZs. The virtual *world* was divided into two smaller Voronoi sections with 5 NFZs governed by a single *Controller* per section servicing 15 *Drones*. A single *Order Generator* created delivery requests, one request every 30s (a deterministic arrival distribution). This setup was designed to achieve high load with an expected duration that did not exceed one hour. Each order was randomly assigned a delivery destination within the *world* and one of two Time Value of Service Delivery functions, illustrated in Figure 1 and inspired by the Amazon payment package model [3], formed the Service Level Agreement between the customer and the service provider. The Time Value of Service Delivery functions, a fixed percentage price reduction for every interval of $t$ time delay, was implemented for ease of computational cost as well as flexibility for future implementation. The *Controller* invokes the LLV algorithm, in parallel to SJF and FCFS, to prioritise each arriving delivery request comprised of the job details, cost payoff function and internally generated task duration distribution[2]. For LLV, the lowest *Net Lost Value* was prioritised.

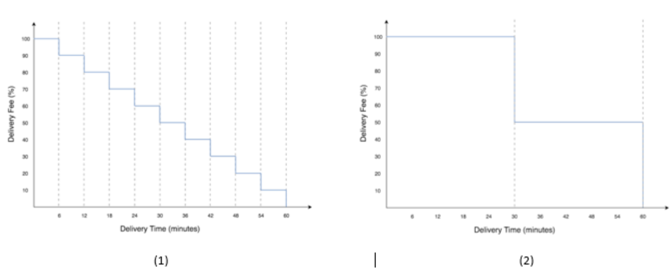


**Figure 1: Time Value of Service Delivery Functions**

[1]A simulation was used in this research given the regulatory limitations and cost constraints inherent in using real-life drones

[2]Delivery duration distribution was determined using the delivery destination, drone speed and historical delivery duration

The simulation was run for a period of 6 hours assuming a non-preemptive scheduling model with a queue size of 40, reordering the requests when a drone became available for delivery. All remaining order requests past the six hour simulation were not scheduled. The assumptions made in this experiment are: (1) *Drone* speed is constant (2) a fixed penalty of £5 for deliveries exceeding an hour (3) The simulation targets "last-mile" logistics, referred to in Section 1, with package deliveries brought to the central controller.

## 3.2 Experimental Results and Discussion

This section discusses the results[3] 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 the algorithms. Figure 2 shows higher queue size load in *Controller 1* than in *Controller 2*. Thus, under overload conditions (*Controller 1*), LLV delivered 48% and 31% more of increased revenue to the service provider than FCFS and SJF, illustrated in Figure 3. On average LLV extracted £1.15 more revenue per delivery request than FCFS and £0.80 than SJF, seen in Figure 4. Interestingly, the enhanced revenue extracted by LLV was not derived from increased deliveries with total deliveries completed by LLV, FCFS and SJF being 850, 859 and 983 respectively as shown in Figure 5, suggesting LLV to be a more efficient model. Without high load conditions (*Controller 2*), LLV did not perform as well as FCFS and SJF, extracting 6% and 10% less revenue respectively.

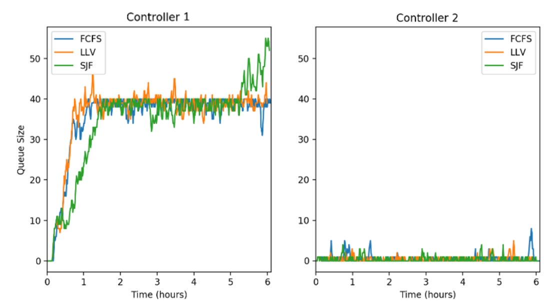


**Figure 2: Queue Size over Time**

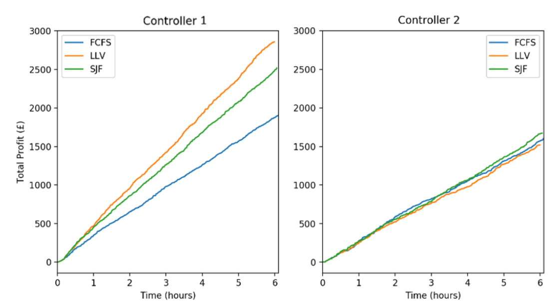


**Figure 3: Total Revenue over Time**

[3]See https://www.doc.ic.ac.uk/~ss11715/DroneSimulationResults/ for detailed simulation results. Simulation workload data is also available in this location.

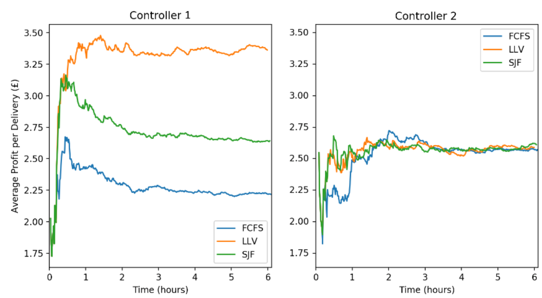


**Figure 4: Average Revenue Per Drone Delivery**

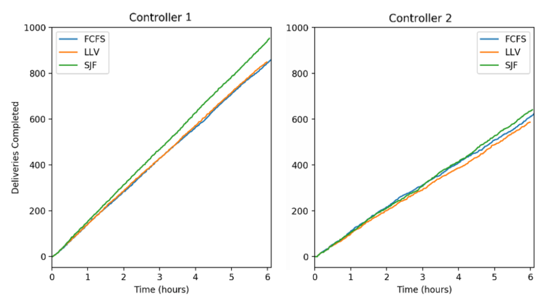


**Figure 5: Completed Deliveries over Time**

The biggest advantage of LLV, highlighted by these results, is firstly 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 successfully into a revenue-driven scheduling model with stochastic service delivery duration. Secondly, LLV can outperform popular scheduling algorithms FCFS and SJF under conditions of high utilisation, beneficial for courier service providers given predictions of increased demand and limited resources highlighted in Section 1. One limitation of LLV is that time spent on LLV's *Net Lost Value* calculation can be large, which then reduces "Value" obtained. However, percentage revenue differences were lower than when under high load, arguably as a result of shorter or earlier deliveries coincidentally having higher "Value", for SJF and FCFS respectively. On the contrary, in highly saturated environments LLV gives a better outcome given the scheduling objective is by design to reduce the *Net Lost Value*.

## 4 CONCLUSION AND FUTURE WORK

Delivery providers are increasingly looking to the skies for solutions to the challenge of light-weight package deliveries. With demand for timely deliveries increasing exponentially from e-commerce, service providers are increasingly convinced that drones are the much needed solution. The experiment results confirm that the novel LLV algorithm bound on the Time Value of Service Delivery function is able to successfully enhance revenue to the service provider, when compared to FCFS and SJF scheduling algorithms, in a time-sensitive drone-delivery network simulation with stochastic service duration times. One avenue for future work would be the application of LLV 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. One complication is the need to use multiple Time Value of Service Delivery functions, as varying views of "value" exists for the same data. Additionally, we could carry out an evaluation of LLV behaviour using a more varied set of Time Value of Service Delivery function types.

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