

## MIT Open Access Articles

### *Efficiency and Fairness in Unmanned Air Traffic Flow Management*

The MIT Faculty has made this article openly available. **Please share** how this access benefits you. Your story matters.

**Citation:** Chin, Christopher, Gopalakrishnan, Karthik, Egorov, Maxim, Evans, Antony and Balakrishnan, Hamsa. 2021. "Efficiency and Fairness in Unmanned Air Traffic Flow Management." IEEE Transactions on Intelligent Transportation Systems, 22 (9).

**As Published:** 10.1109/TITS.2020.3048356

**Publisher:** Institute of Electrical and Electronics Engineers (IEEE)

**Persistent URL:** <https://hdl.handle.net/1721.1/145272>

**Version:** Author's final manuscript: final author's manuscript post peer review, without publisher's formatting or copy editing

**Terms of use:** Creative Commons Attribution-Noncommercial-Share Alike



# Efficiency and Fairness in Unmanned Air Traffic Flow Management

Christopher Chin, Karthik Gopalakrishnan, Maxim Egorov, Antony Evans,  
and Hamsa Balakrishnan, *Member, IEEE*

**Abstract**—As the demand for Unmanned Aircraft Systems (UAS) operations increases, UAS Traffic Flow Management (UTFM) initiatives are needed to mitigate congestion, and to ensure safety and efficiency. Congestion mitigation can be achieved by assigning airborne delays (through speed changes or path stretches) or ground delays (holds relative to the desired takeoff times) to aircraft.

While the assignment of such delays may increase system efficiency, individual aircraft operators may be unfairly impacted. Dynamic traffic demand, variability in aircraft operator preferences, and differences in the market share of operators complicate the issue of fairness in UTFM. Our work considers the fairness of delay assignment in the context of UTFM. To this end, we formulate the UTFM problem with fairness and show through computational experiments that significant improvements in fairness can be attained at little cost to system efficiency. We demonstrate that when operators are not aligned in how they perceive or value fairness, there is a decrease in the overall fairness of the solution. We find that fairness decreases as the air-ground delay cost ratio increases and that it improves when the operator with dominant market share has a weak preference for the fairness of its allocated delays. Finally, we implemented UTFM in a rolling-horizon setting with dynamic traffic demand, and find that efficiency is adversely impacted. However, the impact on fairness is varied and depends on the metric used.

**Index Terms**—Air transportation; Unmanned Aircraft Systems (UAS); UAS Traffic Management (UTM); Traffic Flow Management; fairness; efficiency

## I. INTRODUCTION

THE potential of Unmanned Aircraft Systems (UAS) to dramatically transform societal applications (including infrastructure and environment monitoring, agricultural surveys, communication services, cargo delivery, and even passenger mobility) is expected to lead to a significant increase in autonomous aircraft operations. It has been estimated that by the year 2035, Paris may see as many as 2,500 Urban Air Mobility (UAM) flights, 16,000 delivery drones, and 60 inspection drones flying each hour of the day [1]. Other urban areas are projected to see a 200-fold increase in the number of flights due to Unmanned Aircraft Systems (UAS) operations (autonomous drones for package delivery, sensor measurements, surveillance, tracking, etc.), and a 30-fold increase from UAM operations (autonomous, semi-autonomous, or piloted air taxis) [1], [2]. These operations will be largely

concentrated around dense urban regions, in the proximity of existing airports, and will involve significant investments in technology and infrastructure [3].

The increase in UAS traffic demand will inevitably result in congestion in the air as well as at vertiports (low footprint airports in urban areas designed to support vertical takeoffs and landings). The entire US National Airspace System (NAS) currently handles about 90,000 flights a day, whereas UAS traffic operations are projected to exceed 2.5 million flights per day in the US [4]. The resultant strain on the air transportation infrastructure, if not managed, could result in decreased levels of safety, and increased economic losses and emissions. The increase in vehicle- and system-level autonomy will enable the better utilization of limited resources, but the need for a UAS traffic management system will remain, especially for low-altitude operations. The development of a UAS Traffic Management (UTM) architecture, and the associated protocols, strategies, and infrastructure, is essential for the safe and efficient operations of autonomous aircraft.

Despite the excitement surrounding UAS/UAM operations, several questions regarding UTM architectures remain unanswered. These open problems include the choice between a centralized and a more federated or distributed architecture, the role of a UAS Service Supplier (USS) in managing traffic and interfacing with air traffic controllers, assurances on the quality of service provided to users of the airspace, and the possible timelines for the deployment of UTM solutions [1]. The focus of this paper is the development of strategic traffic flow management techniques for UAS/UAM operations. Prior work has shown that tactical and decentralized conflict resolution protocols are effective at low traffic volumes [5]–[7]; however, they are likely to be less efficient as traffic levels increase. Our work is motivated by the recognition that in high-demand scenarios, centralized resource allocation has the potential to increase overall efficiency and safety. Furthermore, by strategically planning ground holds and airborne trajectory modifications, we can reduce the amount of tactical coordination required of UAS, remote pilots, and USS, thereby improving predictability.

### A. Motivation for UAS Traffic Flow Management (UTFM)

Our approach to UTFM is primarily motivated by four observations. Firstly, in order to scale UAS/UTM operations to meet the increasing demand, it is important to operate efficiently and minimize delays (in this context, delay can be defined as the difference between the desired and actual

C. Chin {chychin}, K. Gopalakrishnan {karthikg} and H. Balakrishnan {hamsa@mit.edu} are with the Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, MA, USA.

M. Egorov {maxim.egorov} and A. Evans {tony.evans@airbus-sv.com} are with Airbus UTM, Sunnyvale, CA, USA.

times of operation). Secondly, the equitable and fair allocation of airspace resources is important, especially in the presence of a large number of aircraft operators; yet, fairness is often the first casualty in the quest for efficiency [8], [9]. Thirdly, UAS operations are likely to result in competing interests and strategic behavior on the part of the various participants, including first-mover advantages and attempts to monopolize the airspace by aircraft operators. It is essential that the airspace, as a public good, remains accessible to all. Finally, the lessons learned from conventional traffic management should be leveraged in the design of a flexible, future-proof next generation aviation infrastructure.

The overarching goals of our approach to UTM are to:

- 1) Explicitly incorporate fairness into traffic flow management decisions while accommodating user-specific fairness requirements.
- 2) Support a range of aircraft operator preferences and vehicle capabilities, as reflected in their delay sensitivity, mission requirements, and operator utility functions.
- 3) Support dynamic traffic demand, thereby enabling novel applications such as on-demand mobility, exploration, quick package delivery, etc.

### B. Prior work

The UTM problem is an extension of the conventional Air Traffic Flow Management (ATFM) problem, which can be used to assign ground delays and speed restrictions to scheduled flights, in order to mitigate congestion [10]–[12]. The optimal assignment of ground delays and airborne delays to flights can be formulated as a large-scale optimization problem. Recent efforts have resulted in tractable approaches to this classical problem [13], [14].

Fairness in allocating scarce airport resources has been explored in prior work [15], [16]. With regard to jointly allocating airport and airspace resources (as in ATFM), three notions of fairness have been defined: reversals [17], overtakings [17], and time-order deviation [18]. Related work in ensuring fair trajectory-based operations has considered max-min fairness [19], cost-penalty formulations [20], as well as notions of accrued delay [21]. This extensive body of work emphasizes the importance that the aviation community has placed on fairness and the wide range of meaningful definitions of fairness in this context. Our work considers these different notions of fairness in the context of UTM and highlights the differences between them.

The UTM problem has been the topic of recent research [6], [14]. While [6] addresses the problem by assigning flights to different “layers” of the airspace, [14] proposes a distributed solution approach based on column generation. Although fairness has been widely recognized as an important criterion [1], [9], it has only recently been explored in the context of UTM and, even then, only for decentralized operating paradigms [5], [22]. The limited work on addressing fairness in strategic UTM has involved monetary transactions, which raises other practical challenges [23]. Furthermore, challenges such as individual vehicle or aircraft operator preferences over delays, fairness, and the lead-time for filing preferred trajectories, have not been previously explored.

### C. Contributions and main findings

This paper makes two key contributions to UTM research. Firstly, we develop a UTM framework that incorporates fairness, user preferences, and dynamic trajectory requests into the decision-making process. Secondly, we evaluate our UTM formulation using UAS/UTM demand generated from an industry-developed simulator, identify appropriate metrics for fairness, and quantify the efficiency-fairness tradeoffs, in the presence of operator preference variability and dynamic traffic demand.

Our main insights on the interplay between fairness and efficiency in UTM can be summarized as follows:

- 1) Although several reasonable notions of fairness can be proposed in a networked setting, they are not all equally easy to achieve in practice. More precisely, we show that some of the metrics may be orthogonal to each other and that optimizing for one may adversely affect another.
- 2) The preferences of different operators can vary in a range of ways (e.g., their preferences may be aligned but differ in magnitude, or they may be misaligned), and the resulting impacts on system efficiency and fairness can differ. More specifically, for the case of two aircraft operators, we find that:
  - As the ratio of the airborne holding cost to the ground holding cost increases, the fairness of the UTM solutions decreases.
  - The greater the divergence between the fairness preferences of the two operators (both in terms of the fairness metrics and the weights given to them), the greater is the loss in both system efficiency and fairness.
  - When the operator with a weak preference for fairness has a high market share, the fairness of the resulting solution improves for both operators, relative to the solution where both operators have even market share.
- 3) UTM with a rolling horizon framework leads to lower efficiency and higher time-order deviation; however, the number of reversals is similar.

### D. Outline

In Section II, we define candidate notions of fairness in the context of UTM and identify the challenges that need to be addressed. Section III presents the mathematical formulation of the resulting optimization problem. In Section IV, we describe the setup for the simulations, while in Section V, we discuss the results and findings. Finally, our conclusions and proposals for future work are discussed in Section VII.

## II. UAS/UAM TRAFFIC FLOW MANAGEMENT (UTFM)

In this section, we highlight the three main features of our proposed UTM framework: the consideration of fairness, variable aircraft operator preferences and vehicle capabilities, and dynamic traffic demand.

### A. Fairness considerations

The revision of trajectories to mitigate congestion requires assigning delays to each flight (i.e. the aircraft takes off/lands/accesses a region of airspace at a different time than is desired by its operator). Depending on the desired trajectory of a flight and the capacities of the airspace sectors it traverses, the amount of delay assigned to each flight can be different. Consequently, the objective of maximizing system efficiency is equivalent to minimizing the sum of delay costs for all the flights. The resulting solution, although efficient, could have an uneven distribution of delays across flights and aircraft operators, raising questions of fairness. Additional considerations include ensuring fairness across flights of differing durations, flights traversing different regions of the airspace, and flights with varying performance capabilities.

When there is only one constrained resource (airspace sector or vertiport), First-Come-First-Served (FCFS) at that resource is a reasonable definition of fairness. However, when a single flight traverses multiple congested resources and FCFS is enforced at each of them, the flight may get excessively penalized as delays from the first resource get compounded further downstream in the trajectory (see example in Fig. 1).

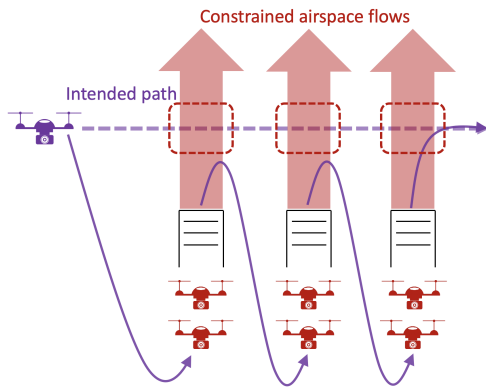


Fig. 1. The purple drone joins the end of the queue at every constrained resource, following a First-Come-First-Serve policy. The dotted purple line denotes the desired trajectory, while the solid purple line denotes the realized one.

Other notions of fairness may be preferable in this networked resource allocation setting. A few examples, which we will describe in greater detail later are:

- 1) As much as possible, maintain the scheduled arrival order of flights at each resource. In other words, if flight  $f_1$  was scheduled to arrive at a resource before another flight  $f_2$ , then we prefer that it does so in the revised schedule. In this case, a reversal is when  $f_2$  arrives at this resource before  $f_1$ . We will formalize this metric of fairness as minimizing the total number of flight-reversals across all resources.
- 2) Find the most constrained resource in a flight's trajectory. This resource would introduce the maximum FCFS delay if it were the only constrained resource present in the trajectory. One could argue that this is the minimum delay that a flight on this trajectory ought to endure, and the optimization should try to minimize, or

at least equalize any delay beyond this minimum value across flights. We will formalize this notion of fairness as minimizing the *time-order deviation (TOD)* for all flights in the schedule.

Several nuances need to be addressed when incorporating fairness into UTFM. A direct consequence of having multiple candidate metrics of fairness is that it is not apparent which one is better, or more widely acceptable to UAS operators. Although intuition would suggest that enforcing some degree of fairness would result in a loss in system efficiency (i.e., the sum of flight delay costs will increase), the nature of this trade-off is not well understood. Furthermore, higher traffic demand, especially in urban areas, would result in a larger number of congestion points (airspace sectors or vertiports) for each flight trajectory. Without explicit planning, the presence of multiple congested resources can significantly decrease the fairness of the UTFM solution (e.g., Figure 1). It is therefore imperative that we incorporate fairness at an early stage of system design, as concerns of unfairness will only grow with traffic volume.

Fairness in the networked setting has been studied in the context of air traffic control flow management [17], [18]. In ATFM, airports typically remain the primary choke points, and the FCFS schedule emerging from a congested airport is usually prioritized over other constraints. However, such a practical approach cannot be translated to UTFM, since there are multiple choke points.

### B. Aircraft operator preferences and vehicle capabilities

While implementing UTFM in practice, one must be cognizant of significant differences that may exist amongst different users of the system. Potential aspects of variability include:

- *Mission requirements.* The *file-ahead time* is how far in advance an operator files a flight plan before the scheduled departure time. UTFM should support on-demand operations with short file-ahead times (e.g., package-delivery or UAM) as well as scheduled operations with long file-ahead times (e.g., planned video inspections or fixed-schedule air taxis). Similarly, some missions such as UAM or package delivery could require flying the shortest path to a destination, while others (e.g., plume tracking or traffic surveillance) could involve hovering or actively sensing and exploring a region.
- *Vehicle capabilities.* Some vehicles may have a wider range of feasible speeds, resulting in a larger potential for airborne holding. Fixed-wing vehicles may not be able to reduce their speed below a certain critical threshold without the risk of stalling, whereas rotary-wing vehicles (like quadcopters) may be able to hover at a particular location and reduce their lateral speed to zero if needed. Vehicles may also have different endurance times and abilities to operate safely when subject to delays.
- *Preferred metrics of fairness.* Certain aircraft operators, such as those running supply and logistics missions, may have coordinated flight operations. For instance, one vehicle may bring a certain package to a warehouse and a drone scheduled for later may transport that package to a customer. For such an operator, reversals in the

order of arrivals may be of significant consequence, and they may wish to minimize the number of reversals in the UTFM solution. On the other hand, a point-to-point UAM operator may only be concerned about their on-time performance relative to competitors. A fair allocation would then be one that results in an equitable distribution of delays for any two flights that use the same set of resources. In such cases, minimizing the TOD might be the preferred metric of fairness, rather than minimizing the reversals.

- *Aircraft operator cost/utility functions.* An operator transporting packages might be more sensitive to delays than a leisure drone photographer. Even among the flights managed by the package delivery operator, an aircraft carrying perishable goods may be more delay-sensitive than one carrying non-perishable goods.

Different operator preferences and vehicle capabilities may affect the tradeoffs between fairness and efficiency. Furthermore, the notion of what is considered fair for a pair of operators may be the same (i.e. aligned) or different (i.e. misaligned). This can affect not only the system efficiency, but also determine the extent to which efficiency must be compromised to satisfy fairness preferences of the operators. The challenge lies in developing a UTFM framework that can not only support diverse user preferences and constraints, but also equitably allocate resources. Such a framework would be a significant departure from ATFM, where the vehicle capabilities are relatively homogeneous, and the limited variability in delay costs due to airline-specific factors (such as connecting passengers, crew time-outs, etc.) are handled *post hoc* via the Collaborative Decision Making (CDM) process [15].

In a marked departure from traditional ATFM research, our work quantifies the loss in efficiency and fairness for different operator traffic volumes and preferences (delay sensitivity and fairness requirements) using a UAS/UAM demand simulator developed by Airbus.

### C. Strategic planning with dynamic traffic demand

The last feature of our UTFM framework that we wish to highlight is its ability to adapt to temporally dynamic traffic demand. In particular, we note that the file-ahead times for an aircraft operator (or vehicle) to convey its demand for airspace or airport resources may be very short. Low traffic demand predictability could correspond to two scenarios: missions may be initiated with short lead times (e.g., on-demand UAM or package delivery), or they could be inherently uncertain due to a reactive sensing control loop (e.g., a car chase using a drone, air pollution monitoring, traffic surveillance, etc.). In other words, the file-ahead times could range from a few weeks for scheduled services, to a few seconds for reactive sensing missions.

Unfortunately, strategic planning requires some look-ahead and visibility into future demand. It is challenging to efficiently manage a mix of scheduled as well as dynamic traffic demand. Furthermore, the UTFM problem needs to be solved frequently at scale, in near-real-time, owing to the high volume of UAS/UTM traffic and dynamically changing flight plans. We

address this concern by implementing the UTFM solution iteratively with a receding horizon to account for dynamic demand and variable file-ahead times.

## III. MATHEMATICAL FORMULATION

In this section, we present the main formulation for the UTFM problem. We describe two metrics to measure fairness and show how they can be incorporated in the optimization. We first build off of the classical traffic flow management problem (TFMP) formulation [11].

### A. Setup and Notations

We consider a discrete-time traffic flow management problem. The mathematical notations used in the formulation are described below.

$\mathcal{T}$	: Set of time periods $\{1, \dots, T\}$ of length $\Delta T$
$\mathcal{A}$	: Set of all airports
$\mathcal{S}$	: Set of all airspace sectors
$\mathcal{F}$	: Set of all flights
$\mathcal{O}$	: Set of all operators
$\mathcal{F}^o$	: Set of all flights by operator $o \in \mathcal{O}$
$C(s, t)$	: Capacity of sector $s \in \mathcal{S}$ at time $t$
$A(a, t)$	: Arrival capacity of airport $a \in \mathcal{A}$ at time $t$
$D(a, t)$	: Departure capacity of airport $a \in \mathcal{A}$ at time $t$
$a_f$	: Scheduled arrival time for flight $f \in \mathcal{F}$
$d_f$	: Scheduled departure time for flight $f \in \mathcal{F}$
$\mathcal{S}^f$	: Sequence of sectors in flight $f$ 's schedule
$\mathcal{S}_j^f$	: Next sector after $j$ in flight $f$ 's trajectory
$\mathcal{P}_j^f$	: Sector preceding $j$ in flight $f$ 's trajectory
$orig_f$	: Origin airport for flight $f$
$dest_f$	: Destination airport for flight $f$
$l_{f,s}$	: Minimum time spent by flight $f$ in sector $s$
$M$	: Maximum delay for each flight
$T_j^f$	: Set of feasible time periods for flight $f$ to arrive at resource $j \in \mathcal{A} \cup \mathcal{S}$ (airport or sector)
$\bar{T}_j^f$	: Latest time in the set $T_j^f$
$\underline{T}_j^f$	: Earliest time in the set $T_j^f$
$w_{j,t}^f$	: A binary variable that is 1 when flight $f \in \mathcal{F}$ has arrived at resource $j \in \mathcal{A} \cup \mathcal{S}$ at or before time $t$

### B. Baseline TFMP

The objective function minimizes total delay cost (*TDC*). The expression for total delay cost (*TDC*) is assumed to be of the form  $TDC = \beta(GD^{1+\epsilon} + \alpha AD^{1+\epsilon})$ , where *GD* is ground delay, *AD* is airborne delay,  $\beta$  is delay to cost scale factor, and  $\alpha \geq 1$  is the ratio of airborne delay cost to ground delay cost. Note that  $\epsilon$  makes these costs super-linear in the delay duration, as we prefer even distribution of delays across flights over skewed delay distributions. For example, setting  $\epsilon$  to be a small positive number ( $\leq 0.05$ ) guides the optimization solver to allocate 2 minutes of delay each for two flights rather than 4 minutes of delay to a single flight, even though the total delay would be the same for both solutions. In other words, this super-linear cost structure helps break ties between multiple

solutions that result in the same total system delay. Without loss of generality, we set  $\beta = 1$ .

Since,  $TD = AD + GD$ , we have

$$TDC = \alpha TD^{1+\epsilon} + (1 - \alpha)GD^{1+\epsilon} \quad (1)$$

If the flight departs at time  $t$ , then the ground delay is  $GD = (t - d^f)$ . Also, if the flight lands at time  $t$ , the total delay is  $TD = (t - a_f)$ . Thus, TDC can be re-written in terms of the decision variables  $w$  as

$$\begin{aligned} TDC = & \sum_{f \in \mathcal{F}} \left( \sum_{t \in T_{dest_f}^f} \alpha (t - a^f)^{1+\epsilon} (w_{dest_f,t}^f - w_{dest_f,t-1}^f) \right. \\ & \left. - \sum_{t \in T_{orig_f}^f} (\alpha - 1) (t - d^f)^{1+\epsilon} (w_{orig_f,t}^f - w_{orig_f,t-1}^f) \right) \quad (2) \end{aligned}$$

The key aspect of the formulation that lends computational tractability to larger-scale problems is the choice of the decision variable  $w_{j,t}^f$ , which is a binary variable that is non-decreasing in time (Constraints (3g) and (3h)). Flight  $f$  is said to enter a resource  $i$  (which could be an airport or a sector) at time  $t$  if  $(w_{i,t}^f - w_{i,t-1}^f) = 1$ .

The following constraints must be satisfied:

$$\sum_{f \in \mathcal{F}: orig_f=k} (w_{k,t}^f - w_{k,t-1}^f) \leq D(k, t), \quad \forall k \in \mathcal{A}, t \in \mathcal{T} \quad (3a)$$

$$\sum_{f \in \mathcal{F}: dest_f=k} (w_{k,t}^f - w_{k,t-1}^f) \leq A(k, t), \quad \forall k \in \mathcal{A}, t \in \mathcal{T} \quad (3b)$$

$$\sum_{f \in \mathcal{F}: i \in \mathcal{S}^f, j = \mathcal{S}^f} (w_{i,t}^f - w_{j,t-1}^f) \leq C(j, t), \quad \forall t \in \mathcal{T} \quad (3c)$$

$$w_{i,t}^f = 0, \quad \forall f \in \mathcal{F}, t = \underline{T}_{j-1}^f, i = \mathcal{S} \cup \mathcal{A} \quad (3d)$$

$$w_{i,t}^f = 1, \quad \forall f \in \mathcal{F}, t = \bar{T}_j^f, i = \mathcal{S} \cup \mathcal{A} \quad (3e)$$

$$w_{i,t}^f - w_{j,t-l_f,j}^f \leq 0, \quad \forall f \in \mathcal{F}, t \in T_i^f, \quad (3f)$$

$$i \in \mathcal{S}^f : i \neq orig_f, j = \mathcal{P}_j^f$$

$$w_{i,t-1}^f - w_{i,t}^f \leq 0 \quad \forall f \in \mathcal{F}, i \in \mathcal{S}^f, t \in T_i^f \quad (3g)$$

$$w_{i,t}^f \in \{0, 1\} \quad \forall f \in \mathcal{F}, i \in \mathcal{S}^f, t \in T_i^f \quad (3h)$$

Constraints (3a), (3b), and (3c) enforce departure, arrival, and sector capacities, respectively. Constraint (3d) ensures that a flight does not reach a sector before the earliest feasible time. Analogously, constraint (3e) enforces that a flight must arrive at a sector before the latest feasible time. The minimum time to be spent in each sector is described in Constraint (3f).

### C. Fairness Metrics

We focus on two candidate notions of fairness, which we describe qualitatively below. We then incorporate them into the baseline TFMP formulation.

1) *Reversals* [17]: According to this notion, a fair solution is one in which the relative ordering of arrivals at any resource is preserved according to published schedules. We want to minimize *reversals* in the ordering of flight arrivals at a sector or an airport relative to the originally scheduled ordering.

A few additional variables for incorporating reversals are defined below.

$R^j$  : Pairs of reversible flights

$T_{f,f',j}^r$  : Set of time periods common for flights  $f$  and  $f'$  where a reversal could occur at resource  $j$

$\lambda_r^o$  : Penalty factor for reversals for operator  $o$

We define a new variable  $s_{f,f',j}$  which is 1 if flight  $f'$  arrives before flight  $f$  at resource  $j$ , where  $f$  was scheduled to arrive before  $f'$ , and 0 otherwise. Thus, flight  $f$  suffers from the reversal, but flight  $f'$  benefits. In the objective function, we sum the previously defined  $TDC$  with the total number of reversals suffered by an operator multiplied by a weight  $\lambda_r^o$ .

$$\min TDC + \sum_{o \in \mathcal{O}} \lambda_r^o \sum_{j \in \mathcal{S}, (f,f') \in R^j, f \in \mathcal{F}^o} s_{f,f',j} \quad (4)$$

The following constraint must be satisfied:

$$s_{f,f',j} = \max(0, w_{j,t}^{f'} - w_{j,t}^f) \quad \forall t \in T_{f,f',j}^r \quad (5)$$

2) *Time-order deviation* [18]: In this section, we describe the time-order deviation metric used to quantify fairness. We calculate the first-come-first-serve (FCFS) arrival time  $FCFS_i^f$  for each flight  $f$  at resource  $i$  that it goes through, assuming that  $i$  was the only constrained resource. With FCFS, arrival slots are assigned to flights according to the original schedule ordering. For each flight, we then calculate the maximum FCFS delay  $d_f^{FCFS}$ .

$FCFS_i^f$  : First-come-first-serve arrival time for flight  $f$  at resource  $i$  assuming that  $i$  was the only constrained resource ( $i \in \mathcal{S} \cup \mathcal{A}$ )

$d_f^{FCFS}$  : Maximum FCFS delay for flight  $f$

$c_{TOD}^f(t)$  : Additional delay cost when flight  $f$  is delayed for time  $t$

$\lambda_t^o$  : Penalty factor for time-order deviation for operator  $o$

Just as with the penalty factor for reversals,  $\lambda_t^o$  is operator specific. The intuition behind time-order deviation is as follows. When there are multiple constrained resources, each flight should not expect to incur any less delay than it would incur as a result of only the most constrained resource along its route. In other words, there is a notion of *expected delay*, that every flight is inherently entitled to be assigned, and only delays beyond this expected delay should be equalized among the multiple flights. Thus, for every flight  $f \in \mathcal{F}$ , the maximum delay that it would have been assigned as a result of only the most constraining resource is

$$d_f^{FCFS} \max_{i \in \mathcal{S} \cup \mathcal{A}} FCFS_i^f \quad (6)$$

Thus, the modified optimization problem is

$$\min TDC + \sum_{o \in \mathcal{O}} \lambda_t^o \sum_f \sum_{t=a_f}^T c_{TOD}^f(t) (w_{dest_f,t}^f - w_{dest_f,t-1}^f),$$

$$\text{where } c_{TOD}^f(t) = (\max\{0, t - a_f - d_f^{FCFS}\})^{1+\epsilon}. \quad (7)$$

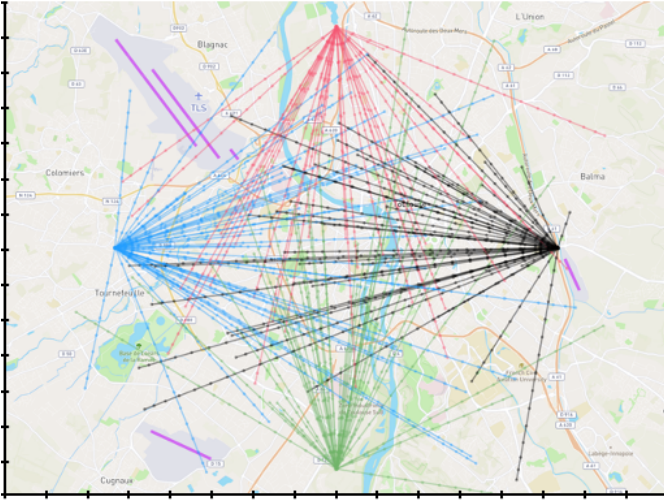


Fig. 2. Example of a four-operator scenario in a 16 km  $\times$  14 km region, with flight trajectories showing the operations flown, the colors denoting different operators, and axis ticks along the border denoting 1km sector boundaries

## IV. EXPERIMENTAL SETUP

### A. Scenario generation

We use a package delivery scenario created by Airbus where four operators in Toulouse, France have warehouses on the outskirts of the city and make deliveries in locations randomly distributed around the city [24]. The demand is generated using a Poisson process. Each flight has a desired 4D trajectory (three spatial dimensions with time as the fourth dimension). For simplicity, only the outbound flight segments, from the warehouse to the delivery site, are considered. We used two demand scenarios: 50 flights/hour and 25 flights/hour per vertiport. Fig. 2 shows the scenario with 50 flights/hour. For some experiments, we use a two-operator scenario, which is generated by combining the black and green operations into one operator and the red and blue operations into another operator.

One of the key requirements of the UTM formulation is that time is discretized into timesteps. We rounded sector entry and exit times to the nearest 60 s (the timestep size) while ensuring that each flight spent at least one timestep in each sector. We set a sector time discretization threshold of 3 s and skip a sector if a flight spent less than 3 s in it. Another requirement of the UTM formulation is that a flight may only traverse through a sector once. There were 8 instances where a flight entered a sector multiple times; for example, it was initially in sector A then briefly left to sector B then reentered A. We eliminated repeated sectors by smoothing the trajectory and forcing the flight to stay in one sector the whole time.

An additional factor that we accounted for was that flights had limited battery capacity, which we assumed to be 20 min. Thus, we used the remaining battery life and the unimpeded time-to-destination to calculate the maximum time duration that a given flight could hold at its current sector at any point in time. This gave a useful upper-bound on airborne delay for each flight at each sector. Table I lists additional parameters.

TABLE I  
LIST OF PARAMETERS

Parameter	Value
Timestep Size	60 s
Sector X-Y Dimensions	1 km $\times$ 1 km
Sector Z Dimension (Height)	65 m
Sector Capacity	1 per sector
Departure Capacity	2 per timestep
Sector Discretization Threshold	3 s
Maximum Battery Life	20 min
Airborne Delay Cost to Ground Delay Cost Ratio	$\alpha = 3$

### B. Fairness-efficiency tradeoffs

We seek to evaluate the fairness-efficiency tradeoff when incorporating one of two fairness metrics: reversals or time-order deviation. We assume that all four operators' notions of fairness are aligned and penalized the same (effectively equivalent to having one operator). Recall that the weight that a fairness metric is given is represented by  $\lambda_r^o$  or  $\lambda_t^o$ . We vary these values to generate fairness-efficiency curves. We use total delay cost as the efficiency metric, as shown in (2). Note that total delay cost is distinct from total delay, as it penalizes airborne delay  $\alpha$  times more than ground delay.

### C. Ratio of airborne to ground delay costs

One of the key parameters in the UTM formulation is the airborne to ground delay cost ratio,  $\alpha$ . When  $\alpha > 1$ , ground delay is preferred over airborne delay. The assumption is that airborne delay is more costly than ground delay because of higher fuel/energy costs. In practice,  $\alpha$  could vary and have a significant impact on not only the split between airborne and ground delay, but also notions of fairness. We evaluate the impact of  $\alpha$  on the baseline UTM and UTM when incorporating reversals and time-order deviation.

### D. Alignment of notions of fairness

We expect that operators will often have not only different  $\lambda$  weights of fairness, but also different notions of fairness. For example, an operator conducting deliveries where the order of operations is very important may care about reversals much more than time-order deviation. The effect of a reversal may propagate downstream to the operators' later operations. On the other hand, an operator passing through multiple constrained resources may care more about time-order deviation (additional delay beyond expected delay) than reversals. We consider a case with two operators where one operator's notion of fairness associated penalty factor is fixed and the other operator's notion of fairness and penalty factor are variable.

### E. Effect of market share

There is concern that the market share of operators may lead to unfair allocations of delay. Smaller operators may be effectively crowded out by larger operators. As an initial step, we evaluate the effect of market share on system and per-operator efficiency and fairness in a case with two operators. We keep the total number of flights constant and randomly select the appropriate number of flights to switch operators. We test several market share splits in a two operator scenario.

### F. Rolling horizon implementation

The standard UTM formulation assumes that the demand is not only deterministic, but also known well in advance. Given the on-demand nature of many UTM applications, this is not a safe assumption. One way around this challenge is to implement a rolling horizon version of the UTM. With a rolling horizon of length  $n$  minutes long, we propose to solve the UTM once for every time-interval of that length (i.e., every  $n$  minutes). Each flight must file their flight plan before the start of the time-interval that contains its scheduled departure time. For example, if  $n = 5$  min, we solve the UTM at 6:00, 6:05, 6:10, and so on. Flights departing between 6:05 and 6:10 must file before 6:05. At 6:05, all flights scheduled to depart between 6:05 and 6:10 are considered for planning (from takeoff to landing), and their revised schedule constrains flights and resource capacities in subsequent time-intervals. For comparison, we also solve the baseline UTM in an on-demand fashion such that one flight is scheduled at a time, in order of their scheduled departure time. We use a scenario with four operators in this case.

## V. RESULTS

### A. Fairness-efficiency tradeoffs

In the baseline formulation, the objective function consists solely of the total delay cost. When incorporating reversals or time-order deviation in the objective function, we expect a trade-off between fairness and efficiency (measured with total delay cost). The total delay cost should either remain unchanged or increase as the fairness terms are added to the objective and drive the solution away from the optimal total delay cost. In return, we expect fairness to increase.

The following figures evaluate two different fairness metrics and two different demand scenarios. Results are shown for a high demand scenario (vertiport demand of 50 flights/hour) and a low demand scenario (25 flights/hour). For each scenario, there is one data point in black for the baseline case, but several data points for reversals and TOD, corresponding to different  $\lambda_r$  and  $\lambda_t$  values, respectively. For this section, we assume that all operators have the same notion of fairness and degree of preference. To conserve space, specific  $\lambda$  values are only shown for one curve in Fig. 3, but the arrow shows the direction in which  $\lambda$  increases.

Fig. 3 plots the average number of reversals and average total delay cost per flight when solving the baseline UTM (“Baseline”) and when incorporating reversals or time-order deviation (“Reversals” or “TOD”). Two baselines are shown, corresponding to the low demand (black square) and high demand scenario (black circle). We first look at the low demand scenario. The blue curve shows the results of incorporating fairness to varying degrees, with the corresponding  $\lambda_r$  value shown next to each point. As  $\lambda_r$  increases, the number of reversals decreases and the total delay cost increases relative to baseline. For small  $\lambda_r$  values, it is possible to reduce the number of reversals with no increase in total delay cost. For example, when  $\lambda_r = 0.4$ , the number of reversals per flight decreases to 0.23 (compared to 0.54 in the baseline) with no increase in total delay cost. With further increases in  $\lambda_r$ ,

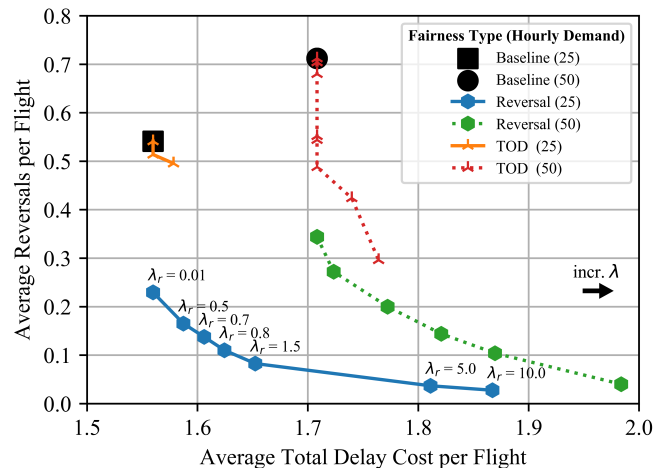


Fig. 3. Reversals vs. Total Delay Cost (TDC) when incorporating different fairness metrics. (The hourly demand level is shown in parentheses.)

decreases in reversals are smaller and become increasingly expensive in terms of the total delay cost. At  $\lambda_r = 10$ , the optimal solution has only 3 reversals (equivalent to an average of 0.03 reversals per flight) but an average delay cost per flight of 1.86 (a 19% increase compared to 1.56 in the baseline). Overall, the average number of reversals decays exponentially with increasing total delay cost. This is because to prevent a pair of flights from being reversed, it may be necessary for one flight to incur excess delay. In the absence of limitations on the maximum delay that a flight can endure, the number of reversals could be driven to zero at the cost of very high total delay.

For small  $\lambda_t$ , incorporating time-order deviation can lead to a decrease in the average number of reversals with little to no increase in the total delay cost, especially for the high demand scenario. However, incorporating time-order deviation does not decrease the average number of reversals as much as explicitly incorporating reversals. For larger  $\lambda_t$ , the optimal solution does not change and no further reductions in reversals are apparent.

In the high demand scenario, the new baseline (shown as a black circle) has a higher average number of reversals and average total delay cost than the previous baseline corresponding to a demand of 25 flights/hour. This is expected, as more congestion leads to more flight interactions and potential for reversals. Incorporating reversals in the objective has a similar effect as doing so with lower demand. The tradeoff curve has a similar shape, and for very high  $\lambda_r$ , the average number of reversals approaches zero while the average total delay cost increases substantially.

Fig. 4 is similar to Fig. 3 but shows the effect on time-order deviation. While penalizing reversals can drive its value to zero, it is not possible to drive the average time-order deviation to zero when minimizing time-order deviation, no matter how large  $\lambda_t$  gets. Recall that time-order deviation is defined as assigned delay minus maximum expected delay (7). There are two ways to reduce system time-order deviation: 1) reduce system total delay or 2) shift delay from flights with



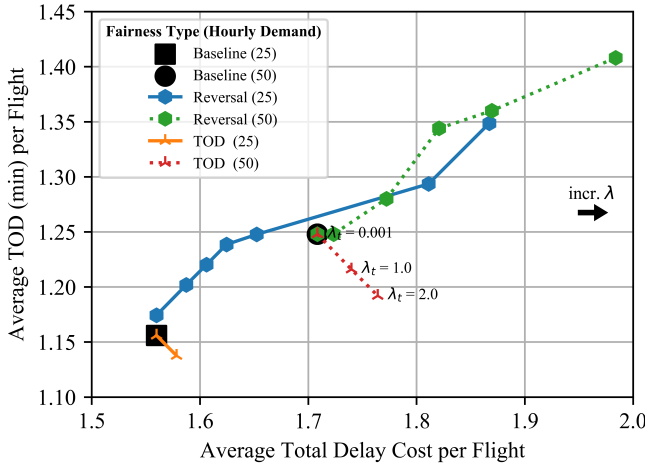


Fig. 4. Time-Order Deviation vs. Total Delay Cost (TDC).

positive time-order deviation to flights with delay less than their maximum expected delay. Thus, when the total delay has been minimized and all flights have delay assigned that is greater than or equal to their maximum expected delay, the time-order deviation has been minimized. This appears to be the case here, as minimizing only the total delay rather than total delay *cost* in the objective function in the high demand scenario leads to an optimal solution with the same 201 min of total delay seen with  $\lambda_t = 2$ . Whereas incorporating time-order deviation can slightly decrease reversals, incorporating reversals results in up to a 17% increase in average time-order deviation in the low demand scenario and up to a 13% increase in the high demand scenario.

While the improvement in the average time-order deviation when penalizing time-order deviation may appear modest, there is another benefit. Since the cost coefficient for time-order deviation is a super-linear function, evenly distributed time-order deviation is preferred over lopsided distributions. As such, incorporating time-order deviation also reduces the standard deviation of time-order deviation across flights. As  $\lambda_t$  increases, the standard deviation decreases;  $\lambda_t = 2$  results in a 27% decrease in the standard deviation of time-order deviation relative to the baseline. As mentioned above, incorporating time-order deviation bounds the loss in efficiency (i.e., increase in total delay cost) while remaining robust to the choice of  $\lambda_t$ . Note how much more total delay cost increases when minimizing reversals compared to when minimizing time-order deviation in Fig. 3 and Fig. 4. These observations suggest that time-order deviation may be a suitable fairness metric in practice.

### B. Effect of the airborne to ground delay cost ratio, $\alpha$

Total Delay Cost (TDC) contains the parameter  $\alpha$ , which is the airborne to ground delay cost ratio. As  $\alpha$  increases, airborne delay gets even more costly relative to ground delay, so ground delay is preferred over airborne delay. This can lead to an increase in total delay minutes, as one minute of airborne delay may be replaced with two minutes of ground delay. We

confirmed this expected behavior. Less obvious is the impact of  $\alpha$  on fairness.

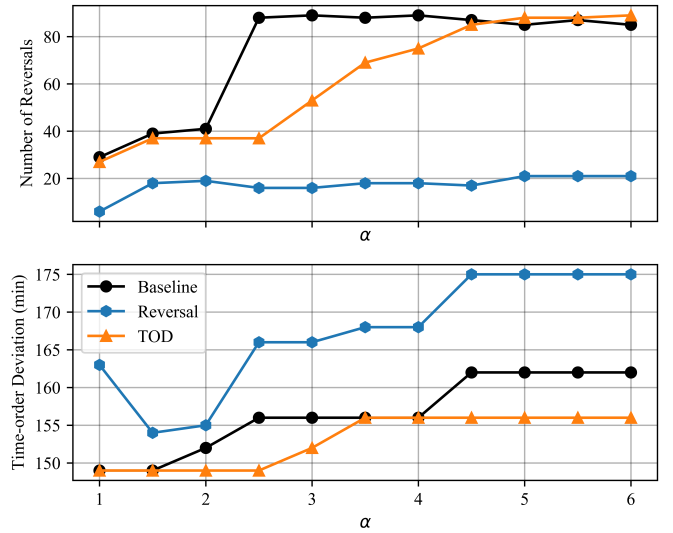


Fig. 5. Impact of the airborne to ground delay cost ratio,  $\alpha$ , on fairness when  $\lambda_r = \lambda_t = 1$ .

Fig. 5 shows fairness/time-order deviation across different  $\alpha$  values when prioritizing different notions of fairness.  $\lambda_r$  and  $\lambda_t$  are both fixed to 1. For all prioritizations, increasing  $\alpha$  generally leads to an increase in reversals and time-order deviation. As delay is shifted from the air to the ground, ground delays are assigned based on the most congested resource in the trajectory. This conservative approach exacerbates the unfairness (e.g. reversals) for all the resources in the trajectory rather than just remaining localized to the congested resource. Thus, when the system can afford airborne delays, there is significant flexibility in assigning delays only when vehicles interact with congested resources. This helps improve the system fairness.

A UTM solution prioritizing a particular fairness metric will naturally perform the best with respect to that metric. This is highlighted in both the subfigures, where the fairest solution (lowest values) are for UTM solutions incorporating reversals (top) and TOD (bottom), in terms of reversals and time-order deviation, respectively. Prioritizing time-order deviation performs better (in terms of number of reversals) than the baseline for  $\alpha < 5$  and slightly worse for  $\alpha \geq 5$ . But prioritizing reversals performs worse than the baseline in terms of time-order deviation for all values of  $\alpha$ .

### C. Misaligned and imbalanced notions of fairness

The previous section described results when all operators have aligned notions of fairness and the same  $\lambda$  weight of fairness. We refer to this scenario as a *perfect alignment* of fairness. However, operators can have different efficiency-fairness trade-off preferences, as reflected by the  $\lambda$  value or different notions of fairness itself (e.g. reversals or time-ordered-deviation). Whenever two operators have the same notion of fairness, they are said to be *aligned*. Whenever two operators have different notions of fairness (e.g., one prefers

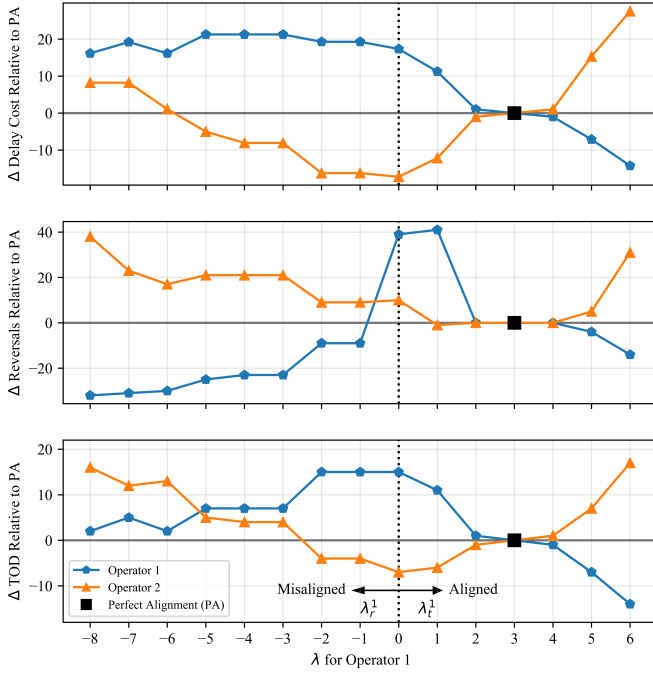


Fig. 6. Operator efficiency and fairness with varying  $\lambda_t^1$  or  $\lambda_r^1$ , with fixed  $\lambda_r^2 = 3$ . Operator 1 and 2 are misaligned when operator 1 prioritizes reversals, aligned when operator 1 prioritizes time-order deviation, and perfectly aligned when  $\lambda_t^1 = \lambda_t^2 = 3$ .

to minimize reversals while the other prefers to minimize TOD), they are said to be *misaligned*. In this experiment, Operator 2 has the same  $\lambda$  weight of fairness for time-order deviation ( $\lambda_t^2 = 3$ ), while Operator 1's notion of fairness and  $\lambda$  weight vary, as shown in Fig. 6. Three subplots show the change in total delay cost, number of reversals, and time-order deviation for each operator relative to a perfect alignment of  $\lambda_t^1 = \lambda_t^2 = 3$ . In this section, we refer to increases/decreases relative to perfect alignment as “increases” and “decreases”, respectively. Starting with the top subplot, we observe that efficiency decreases in two cases: in the misaligned region with the operators having different notions of fairness and in the aligned region with  $\lambda_t^1$  much higher than  $\lambda_t^2$ . In the misaligned region, for  $\lambda_r^1 \leq 5$  the decrease in total delay cost from prioritizing time-order deviation for Operator 2 is overridden by the worsening of total delay cost due to minimizing reversals for Operator 1. For  $\lambda_r^1 > 5$ , total delay cost increases for both operators. In the region near  $\lambda^1 = 0$ , delay cost increases for Operator 1 and decreases for Operator 2, but these mostly balance each other out. In the aligned region where Operator 1 has a stronger fairness preference than Operator 2, Operator 1's decrease in total delay cost is outweighed by Operator 2's increase.

As with efficiency, fairness decreases when one operator has a much stronger notion of fairness than the other operator, in both the misaligned and aligned case. Looking at the middle subplot of Fig. 6, for all misaligned cases, Operator 1's reversals naturally decrease since they are the only one minimizing reversals, and Operator 2's reversals increase. For  $\lambda_r^1 \geq 10$ , the increase in Operator 2's reversals outweighs

Operator 1's decrease leading to an overall increase in number of reversals, but for smaller  $\lambda_r^1$  the total number of reversals decreases. The increase in Operator 1's (and the system) number of reversals peaks around  $\lambda^1 = 0$ . This is because Operator 1 has weak fairness preferences for either reversals or time-order deviation, and minimizing either could reduce the number of reversals. Moving onto the bottom subplot of Fig. 6, in the misaligned region, Operator 1's preference of minimizing reversals increases time-order for both operators. In the aligned region, Operator 1's time-order deviation increases if its fairness weight is lower than Operator 2's but decreases if its fairness weight is higher.

#### D. Effect of market share

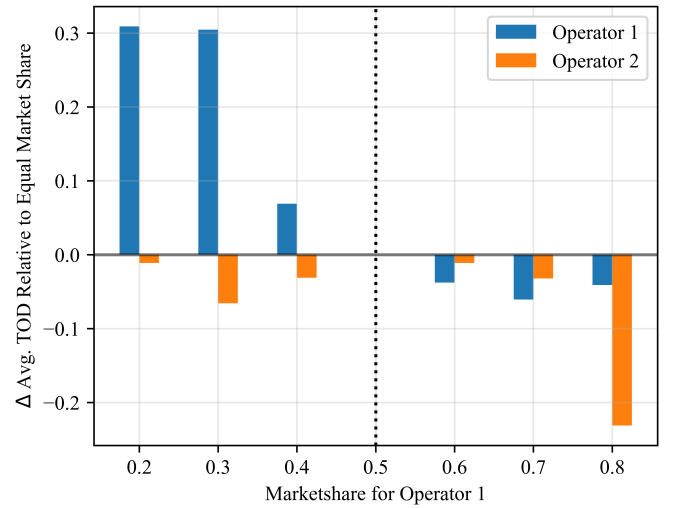


Fig. 7. Effect of market share on Time-Order Deviation, with fixed  $\lambda_t^1 = 0.5$ ,  $\lambda_t^2 = 1.0$ .

To test the effect of market share on fairness, we fix the fairness parameters in a two-operator setting. In this scenario, both operators care about time-order deviation, but Operator 1 has a weaker preference for fairness than Operator 2 ( $\lambda_t^1 = 0.5$  and  $\lambda_t^2 = 1$ ). We then vary the market share of Operator 1 from 0.2 to 0.8 in increments of 0.1, as seen on the x-axis of Fig. 7. We switch the designated operator of an appropriate number of random operations to create a scenario with any given market share split. We run 50 experiments for each market share split, with each experiment having the same number of flights per operator, but different flights belonging to each operator. The y-axis of Fig. 7 shows the change in average time-order deviation relative to average time-order deviation with equal market share on the y-axis. Fairness improves for both operators when the operator with weak fairness preference (Operator 1) has a higher market share and the operator with strong fairness preference (Operator 2) has a low market share. In contrast, the fairness of Operator 1 deteriorates if its market share is reduced.

One way to rationalize this is as follows. If an operator has a very high  $\lambda$  (e.g., Operator 2) but a low market share, it will be relatively easy to accommodate their requests without

penalizing other operators. On the other hand, if the market share of this operator was high, then the overall solution would preferentially satisfy the fairness requirements of this operator and might have to impose excessive penalties (in terms of efficiency and fairness) on others.

### E. Rolling horizon implementation

In this section, we discuss the results when using a rolling horizon of varying size for the high demand scenario (50 flights/hour). In Fig. 8, the total number of reversals vs. the total delay cost is shown for the case with no rolling horizon (“Deterministic”), identical to the previous section, and cases with 15-minute and 5-minute rolling horizons. Note that fairness is only incorporated among the flights that are planned in a given horizon. We also show the result for solving the UTFM such that one flight is scheduled at a time in order of their scheduled departure time (“Myopic UTFM”).

We first look at the impact of the rolling horizon in the baseline case (no fairness metric incorporated). Recall that in our implementation of the rolling horizon, flights from the previous time step cannot be changed, eliminating the ability to shuffle those flights with flights from the current time step. While this lowers the number of reversals, it comes at the expense of total delay cost. Thus, compared to the deterministic baseline, both of the rolling horizon baselines (15-minute and 5-minute horizons) have a lower number of reversals and a higher total delay cost. Flights are planned for the 5-minute rolling horizon with even less information than with the 15-minute rolling horizon; thus, it is not surprising that the total delay cost for the 5-minute rolling horizon is greater than that of the 15-minute rolling horizon. The on-demand case has, by far, the highest total delay cost, which makes sense given that UTFM is only solved for one flight at a time. The solution results in 67 reversals, higher than the 15-minute rolling horizon but lower than the 5-minute rolling horizon.

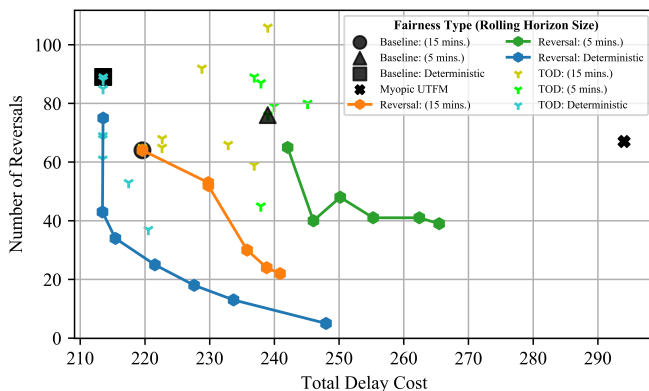


Fig. 8. Reversals vs. Total Delay Cost (TDC), by length of rolling horizon. “Myopic” is when flights are planned one-by-one in order of scheduled time of departure.

The 15-minute rolling horizon (depicted with orange hexagon points) is similar to the deterministic case, except the decrease in fairness (reversals) is not exponential but

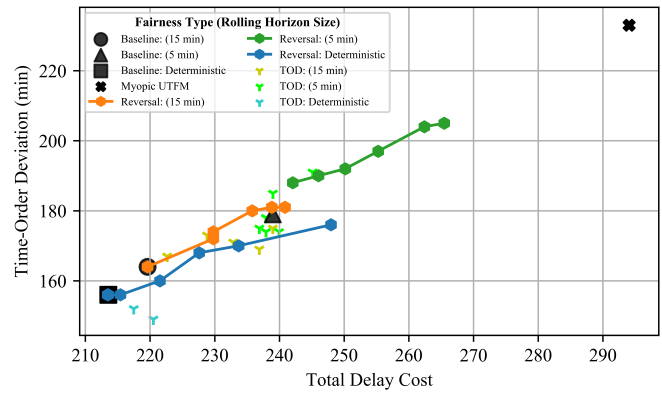


Fig. 9. Time-Order Deviation vs. Total Delay Cost (TDC), by length of rolling horizon.

close to a linear decrease. Incorporating time-order deviation generally increases the number of reversals. With the 5-minute rolling horizon, incorporating reversals (green hexagon points) follows the expected behavior: decreasing number of reversals for increasing total delay cost. Also, the number of reversals plateaus after very little increase in total delay cost. This is likely since fewer flights in each time step results in less leeway to adjust schedules to untangle reversals. The myopic case again has the highest total delay cost but also has much higher time-order deviation than all other results.

Fig. 9 is similar to Fig. 8 but shows time-order deviation instead of reversals on the y-axis. When comparing the baseline points (in black), time-order deviation increases as the horizon size decreases. As seen before, incorporating reversals increases time-order deviation, and this trend is seen across all horizon sizes tested. On the other hand, incorporating time-order deviation decreases time-order deviation in the deterministic case and has more mixed results with the 5-minute and 15-minute rolling horizons.

An important consideration of the rolling horizon implementation is the runtime, which we define as the computational time to optimize all the traffic demand (flights). As the horizon size increases, more flights are included in each time-interval, adding additional variables to the TFMP formulation and leading to a longer runtime. On the other hand, a larger horizon size means that fewer subproblems need to be solved. For example, the simulation lasts 87 min, so with a horizon size of 45 min, just two horizons (with several flights) are needed. In contrast, with a horizon size of 5 min, 18 horizons (each with fewer flights) are needed.

Fig. 10 shows how runtime varies for different horizon sizes when incorporating either reversals or time-order deviation (TOD). The runtime for the deterministic solution (i.e., all flights are known in advance) is also shown. With time-order deviation, total runtime decreases exponentially as horizon size increases. With reversals, runtime decreases as horizon size increases from 5 to 25 min, but increases thereafter. The TFMP formulation with reversals requires more variables than the formulation with time-order deviation, and therefore takes longer to solve for a larger number of flights. For all scenarios tested, the total runtime is reasonable (at most about 5 min)

considering that the simulation spans nearly 90 min.

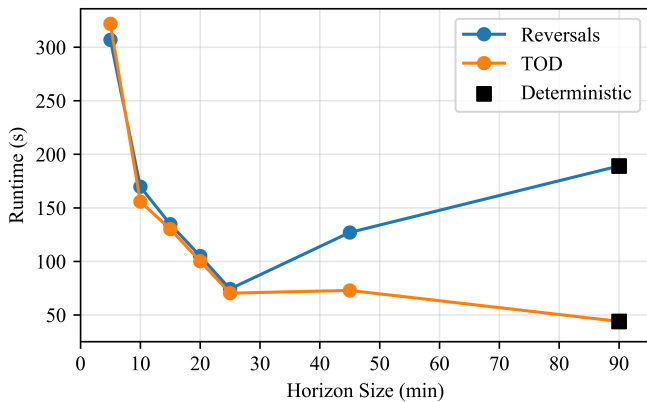


Fig. 10. Runtimes for different rolling horizon sizes.

## VI. DISCUSSION OF RESULTS

### A. Other metrics of fairness

A metric of fairness closely related to reversals is overtakings [17]. It quantifies the magnitude of reversals, i.e. measures the minutes by which a flight  $f_1$  arrives before an earlier scheduled flight  $f_2$  at a particular airspace sector or vertiport. Qualitatively, minimizing the total overtakings in the system is very similar to minimizing reversals; this is backed up with experimental evidence, but is not shown in this paper for brevity (see [25]). A consequence of these two metrics being closely related is that individually optimizing for either one results in improvements in the other metric also. Essentially, paying a price in efficiency for either of the metrics gets you the other for “free”.

Reversals and overtakings are two fairness metrics that have the potential to be achieved in an absolute sense. By that, we mean that the total number of system reversals or overtaking minutes can be driven to zero, if there were no constraints on the maximum delay for each vehicle. This is in contrast with a metric like TOD, where even a massive loss in efficiency may not result in a TOD value of zero. Thus, one could present the case for using metrics similar to TOD in practice, since they are more resilient to poor design choices of  $\lambda$ , and enable a framework that limits inefficiency while incorporating fairness.

Another approach is to perform a *First-Scheduled-First-Served* allocation for each flight arriving at a constrained resource. Under this approach, when a flight is excessively delayed at its first constrained resource and reaches the second resource, it does not simply join the end of the queue; instead, the scheduled time of arrival at that resource determines the priority ordering at the queue. This reduces the occurrence of “double penalties” where flights are delayed at one sector and then further delayed at downstream sectors.

Lastly, we would like to highlight another natural definition of fairness, the minimization of the variance in delays across flights. This can be achieved by penalizing total delays exponentially by setting a high  $\epsilon$  in the baseline UTFM formulation. When  $\epsilon$  is high, the optimal solution will tend to achieve a min-max fair solution, where it attempts to minimize the maximum

delay. The key takeaway from this discussion is that while there are several reasonable notions of fairness, they can be easily incorporated in the UTFM formulation.

### B. Implementing UTFM in a receding horizon framework

There are several nuances to implementing UTFM in a dynamic traffic demand scenario, as each trajectory request can come with a different file-ahead time. Such scenarios can lead to interesting questions regarding the extent to which UTFM should aggregate the demand to improve efficiency and fairness, while at the same time not being too aggressive in the aggregation such that it induces artificial inefficiencies.

One possible implementation framework would be to aggregate all requests within a fixed time interval, say  $T_{\text{plan}}$ , and solve the UTFM problem. However, in the extreme case that a vehicle files a request right after an interval is planned, it would have to endure an artificial delay of  $T_{\text{plan}}$  even before it is assigned a revised trajectory. However, if a vehicle always files ahead, with at least  $T_{\text{plan}}$  buffer, then its requested schedule is guaranteed to be considered by the UTFM as filed (an assumption we make when presenting our results in Section V-E).

A possible modification to the above strategy to eliminate the artificial delays would be to solve the aggregate UTFM problem for flights that file sufficiently ahead, but then follow a *Myopic UTFM* strategy for flights with low file-ahead times. While this sacrifices fairness and does not help capitalize on the efficiency gain due to coordinated planning, it would eliminate adding artificial delays.

In our current implementation, once a flight is scheduled, its schedule is fixed and it acts as a constraint to subsequent flights. If we allow flights to be re-planned (potentially changing delay assignments), we may be able to improve efficiency and fairness. In ATFM there are practical human factors limitations to how often flights can be re-planned; the increased autonomy of UAS is likely to eliminate these concerns.

### C. Varying aircraft operator delay utility functions

Our method is also adaptable and can minimize any utility function that represents flight delay costs. We have also shown in our experiments that it is easy to incorporate operator- or even flight-specific utility functions for the delays. In Section V, we used a marginally super-linear delay cost function (to break ties and prefer a delay of 3 min each to two flights over a delay of 6 min to a single flight), but that need not be the most representative for all operators.

One reasonable utility function  $U_i$  that an operator  $i$  with delay  $D_i$  would like to minimize is [22]:

$$U_i(D_i) = \begin{cases} \beta_1 \sqrt{D_i}, & \text{if } D_i < D_{\text{indifferent}} \\ \beta_2 D_i, & \text{if } D_{\text{indifferent}} \leq D_i < D_{\text{intolerable}} \\ \beta_3 D_i^2, & \text{if } D_i \geq D_{\text{intolerable}} \end{cases}$$

where  $\beta_1$ ,  $\beta_2$  and  $\beta_3$  are constants that ensure continuity of the utility function. Other possible options involve step functions (representing a sharp increase beyond a threshold which can

happen due to cancellations), constant utility function (representing irrelevance of delays for applications such as aerial photography), or exponential functions (for extremely time-sensitive missions).

The utility function is incorporated into the formulation by specifying the total delay cost as  $c_{\text{total}}^f(t) = U_i(t)$ ,  $\alpha = 1$  and eliminating the ground hold reduction  $c_g^f = 0$ . Although not highlighted in our examples, the delay utility function can also depend on both the ground and the air delay. An interesting consequence of this formulation is that the complexity of solving the optimization does not change depending on the nature (e.g. linear, non-linear, convex, non-convex etc.) of the utility function.

## VII. CONCLUSIONS

This paper explored the UAS/UTM traffic flow management problem with a special emphasis on the efficiency and fairness of the resultant solution. In particular, we focused on the impact of aircraft operators' preferences, airborne to ground delay cost ratios, and market shares on fairness. We considered two metrics of fairness: the number of reversals and time-order deviation. We found that it is possible to improve either of these fairness metrics at little cost to efficiency (i.e. little increase in total delay cost). We also found that while minimizing reversals, time-order deviation increases, but when minimizing time-order deviation, the number of reversals could also decrease.

We also evaluated the impact of aircraft operator preferences on fairness and showed that as the airborne to ground delay cost ratio increases, fairness decreases. In a two-operator setting, system efficiency and fairness are both at their best when the two operators have the same notion of fairness and value them to similar degrees. Additionally, fairness improves when the operator with dominant market share has a weak preference for fairness. Finally, we considered UTM in a rolling horizon setting with dynamic traffic demand, and found that efficiency and time-order deviation worsen at shorter horizons, while the number of reversals is unaffected.

We are currently pursuing several extensions of this research. We are looking at how operator delay cost functions impact efficiency and fairness, particularly when operators have different delay costs. We are also adapting the rolling horizon framework to include the re-planning of airborne flights that have already been scheduled. This approach would be useful in scenarios where flights do not comply with their assigned 4-D trajectories. We also intend to test scenarios with heterogeneous operators (e.g., simultaneous urban air mobility and package delivery operations). Finally, we are interested in investigating the impacts of strategic (gaming) behavior on the part of the aircraft operators on fairness.

## ACKNOWLEDGMENTS

This work was supported in part by A<sup>3</sup> by Airbus under contract number 40008574, and by NASA under grant number 80NSSC19K1607.

## REFERENCES

[1] K. Balakrishnan, J. Polastre, J. Mooberry, R. Golding, and P. Sachs, "Blueprint for the Sky: The roadmap for the safe integration of autonomous aircraft," Airbus UTM, Tech. Rep., 2018.

[2] M. Doole, J. Ellerbroek, and J. Hoekstra, "Drone delivery: Urban airspace traffic density estimation," 2018.

[3] P. D. Vascik, R. J. Hansman, and N. S. Dunn, "Analysis of urban air mobility operational constraints," *Journal of Air Transportation*, vol. 26, no. 4, pp. 133–146, 2018.

[4] R. Sengupta, "Aviation = aircraft + airspace consumerizing airspace," in *USA/Europe Air Traffic Management R&D Seminar*, June 2015.

[5] L. Sedov, V. Polishchuk, and V. Bulusu, "Decentralized self-propagating ground delay for UTM: Capitalizing on domino effect," in *2017 Integrated Communications, Navigation and Surveillance Conference (ICNS)*. IEEE, 2017, pp. 6C1–1.

[6] L. Sedov and V. Polishchuk, "Centralized and distributed UTM in layered airspace," in *8th ICRAT*, 2018.

[7] J. E. Holland, M. J. Kochenderfer, and W. A. Olson, "Optimizing the next generation collision avoidance system for safe, suitable, and acceptable operational performance," *Air Traffic Control Quarterly*, vol. 21, no. 3, pp. 275–297, 2013.

[8] J. Rios, "Strategic deconfliction: System requirements," *NASA UAS Traffic Management (UTM) Project*, 2018.

[9] T. Prevot, J. Rios, P. Kopardekar, J. E. Robinson III, M. Johnson, and J. Jung, "UAS traffic management (UTM) concept of operations to safely enable low altitude flight operations," in *16th AIAA Aviation Technology, Integration, and Operations Conference*, 2016, p. 3292.

[10] A. R. Odoni, "The flow management problem in air traffic control," in *Flow control of congested networks*. Springer, 1987, pp. 269–288.

[11] D. Bertsimas and S. S. Patterson, "The air traffic flow management problem with enroute capacities," *Operations research*, vol. 46, no. 3, pp. 406–422, 1998.

[12] G. Lulli and A. Odoni, "The European Air Traffic Flow Management Problem," *Transportation Science*, vol. 41, no. 4, pp. 431–443, November 2007.

[13] D. Bertsimas, G. Lulli, and A. Odoni, "An integer optimization approach to large-scale air traffic flow management," *Operations research*, vol. 59, no. 1, pp. 211–227, 2011.

[14] H. Balakrishnan and B. G. Chandran, "A distributed framework for traffic flow management in the presence of unmanned aircraft," in *USA/Europe Air Traffic Management R&D Seminar*, June 2017.

[15] B. Kotnyk and O. Richetta, "Equitable models for the stochastic ground-holding problem under collaborative decision making," *Transportation science*, vol. 40, no. 2, pp. 133–146, 2006.

[16] T. Vossen, M. Ball, R. Hoffman, and M. Wambsgans, "A general approach to equity in traffic flow management and its application to mitigating exemption bias in ground delay programs," *Air Traffic Control Quarterly*, vol. 11, no. 4, pp. 277–292, 2003.

[17] D. Bertsimas and S. Gupta, "Fairness and collaboration in network air traffic flow management: an optimization approach," *Transportation Science*, vol. 50, no. 1, pp. 57–76, 2015.

[18] C. Barnhart, D. Bertsimas, C. Caramanis, and D. Fearing, "Equitable and efficient coordination in traffic flow management," *Transportation science*, vol. 46, no. 2, pp. 262–280, 2012.

[19] O. Rodionova, H. Arneson, B. Sridhar, and A. Evans, "Efficient trajectory options allocation for the collaborative trajectory options program," in *2017 IEEE/AIAA 36th Digital Avionics Systems Conference*. IEEE, 2017.

[20] I. del Pozo de Poza, M. Vilaplana Ruiz, and C. Goodchild, "Assessing fairness and equity in trajectory-based operations," in *9th AIAA ATIO Conference (ATIO)*, 2009.

[21] H. Idris, C. Chin, and A. D. Evans, "Accrued delay application in trajectory-based operations," in *USA/Europe Air Traffic Management R&D Seminar*, 2019.

[22] A. D. Evans, M. Egorov, and S. Munn, "Fairness in Decentralized Strategic Deconfliction in UTM," in *AIAA Scitech 2020 Forum*, 2020, p. 2203.

[23] B. Skorup, "Auctioning airspace," *Mercatus Research Paper*, 2018.

[24] M. Egorov, V. Kuroda, and P. Sachs, "Encounter aware flight planning in the unmanned airspace," in *2019 Integrated Communications, Navigation and Surveillance Conference (ICNS)*, 2019.

[25] C. Chin, K. Gopalakrishnan, H. Balakrishnan, M. Egorov, and A. Evans, "Tradeoffs between efficiency and fairness in unmanned aircraft systems traffic management," in *9th International Conference on Research in Air Transportation*, 2020.