

Tradeoffs between Efficiency and Fairness in Unmanned Aircraft Systems Traffic Management

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Abstract—The growing use of drones and other Unmanned Aircraft Systems (UAS) is expected to make airspace resources more congested, necessitating the use of UAS Traffic Management (UTM) initiatives to ensure safe and efficient operations. The core functions of UTM are to prevent the loss of airborne separation and to mitigate congestion at departure or arrival points. These functions can be achieved through revising the schedule by assigning airborne delays (speed changes or path stretches) or ground delays (delayed takeoff times) to aircraft.

Our work evaluates the fairness aspects of delay assignment while attempting to achieve more efficient UTM. Dynamic and high traffic demand, variability in UAS operators’ preferences, and differences in vehicle capabilities can adversely impact the fairness of the revised schedule. We show through computational experiments that, for certain fairness metrics, significant improvements in fairness can be attained with very little decrease in system efficiency. We also quantify the tradeoff between efficiency and fairness under dynamic demand, when trajectories are incorporated in a rolling horizon framework.

Keywords: *Fairness; Equity; Efficiency; Air Traffic Flow Management; UAS Traffic Management*

I. INTRODUCTION

The increasing demand for Unmanned Aircraft Systems (UAS) and Urban Air Mobility (UAM) applications, such as package delivery, aerial sensing, and air taxis, is expected to dramatically transform air traffic. Recent studies estimate that there will be demand for over 170,000 package-delivery drone flights/hour over Paris by the year 2035, with some urban areas projected to see a $200\times$ increase in the number of flights due to UAS operations, and a $30\times$ increase from UAM operations [1, 2]. These projections illustrate the critical need for UAS Traffic Management (UTM) approaches to mitigate congestion and ensure safety. Due to the dynamic and unscheduled nature of UAS/UAM demand, any UTM system will need to employ both tactical (i.e., near real-time) and strategic (i.e., minutes or hours in advance) techniques to ensure the safe separation of aircraft, to avoid congestion in the airspace and at take-off/landing zones (vertiports), and to improve system efficiency.

This paper considers the strategic aspects of UTM, with a particular focus on the tradeoffs between system efficiency and fairness to aircraft operators. The starting point of our research is the significant body of related prior work on air traffic flow management (ATFM), which has focused on conventional aircraft. The key idea behind ATFM is to proactively manage congestion by anticipating traffic demand and predicting the usage of various airspace and airport resources, with respect to their capacities. Delays are then assigned to aircraft, either before departure (i.e., on the ground) or in the air (through airborne holds or speed changes), in order to meet resource capacity constraints. The overarching objective of ATFM is to improve system efficiency by reducing the total delay, and by absorbing unavoidable delays on the ground, where they are less costly, rather than in the air.

The revised schedule that minimizes system delay may unevenly distribute delay between different flights or operators. Also, the optimal solution may increase schedule reversals, wherein a flight f_1 arrives at a resource before another flight f_2 , which was originally scheduled to arrive at that resource before f_1 . These scenarios capture a notion of *unfairness*, where certain flights are more delayed than others or the schedule order deviates from the first-scheduled first-served sequence. A key challenge while considering fairness in UTM is that there are multiple reasonable definitions of fairness. Furthermore, the different notions of fairness may not be aligned.

Enforcing a notion of fairness could result in a loss in efficiency. For instance, barring maximum delay limits, flights could be delayed indefinitely to ensure first-scheduled-first-served ordering. Thus, one can consider a spectrum of constraints, ranging from no fairness considerations to complete fairness in the revised schedule. As fairness levels increase, the system efficiency, measured in terms of total delay, is expected to decrease.

A. Motivation

This paper adapts solutions to the classic ATFM problem to the UTM context. The focus of our analysis is fairness, which has been recognized as a key consideration by industry stake-

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holders and regulators [3]. If fairness is not addressed, the system will benefit first-movers or large operators of UAS, stifling new entrants. Additionally, the system may incentivize strategic behavior (e.g., filing ‘fake’ UAS missions, or exaggerating vehicle limitations) that compromises safety and efficiency. In addition, an organization could be a UAS Service Supplier (USS) as well as a UAS operator in the same airspace. Policies that ensure a certain degree of fairness are thus needed to prevent the monopolization of airspace. Finally, it is preferable to consider fairness while discussions about UTM architectures are at their infancy, rather than later in a post hoc manner. In summary, our work helps address the following questions: What are the trade-offs between efficiency and fairness in UTM? Can we quantify the loss in efficiency when incorporating varying degrees of fairness? What are different notions of fairness and are some more preferable than others?

B. Prior Work

The efficient allocation of constrained airspace and airport resources has been studied extensively, from a single-airport scenario to the entire system. Fairness and equity have been considered in the context of arrivals at a capacity-constrained airport [4, 5]. The ATFM problem, which considers both airspace and ground resources, is more challenging to address; however, significant progress has been made in solving this problem over the past two decades [6, 7, 8].

Fairness in ATFM has previously been defined in terms of three popular metrics: reversals [9], overtakings [9], and time-ordered-deviation [10]. Several definitions of fairness have also been proposed and analyzed in the context of trajectory-based operations. For instance, max-min fairness [11], cost-based penalization for fairness and equity [12], and accrued delay [13] have been considered. This paper complements these works by showing that some of these metrics may be aligned, whereas others may measure fairness along relatively orthogonal dimensions.

The study of fairness in the UTM context [14] is a nascent field. Proposed ideas include auctioning the airspace [15] or introducing fairness in decentralized operations [16]. While there has been recent work on federated and distributed approaches to UTM [8], this paper considers fairness in a centralized setting.

C. Contributions and Main Findings

The contributions of this paper are threefold. First, we identify the nuances of the UTM context that prevent the direct application of ATFM solutions. Second, our work emphasizes that there is no all encompassing metric of fairness, and that the choice of metric may be critical in determining the optimal allocation of resources. Finally, we use realistic simulations, including trajectory data from an Airbus simulator, battery-life-based flight time constraints, dynamic demand with low file-ahead times, and a rolling horizon implementation to evaluate the tradeoffs between efficient and fair solutions in a practical UTM setting.

Our major findings are as follows:

- 1) Depending on the fairness metric, a significant improvement in fairness can be obtained in exchange for little to no decrease in system efficiency.
- 2) Some fairness metrics may be aligned in the sense that they can be jointly optimized and improved upon. On the other hand, other fairness metrics may be misaligned, and optimizing one may worsen another.
- 3) Dynamic demand, or demand with low file-ahead times, can be incorporated in the TFMP by using a rolling horizon framework. However, a rolling horizon framework reduces system efficiency. Interestingly, fairness of the solution may improve or worsen, depending on the metric.

II. UAS/UAM TRAFFIC FLOW MANAGEMENT (UTFM)

ATFM in the context of UTM poses a set of unique challenges that are not present in the original problem.

A. Confounding Factors in UTM

Unlike airlines, UAS/UAM operators are likely to have a wider range of preferences based on their mission requirements and vehicle capabilities. For instance, the delay cost of a package delivery mission may be very different from that of an aerial pollution monitoring platform. Vehicles with limited range and endurance, or even fixed wing drones, may be more sensitive to airborne delays, speed restrictions, or holds, as compared to rotary wing drones. Secondly, UTM demand is expected to be highly dynamic, making it more difficult to anticipate the usage of airspace and vertiport resources. UAS operators may also file their flight plans with short, and varying advance notice. The UTM system needs to support such on-demand mobility applications. Finally, the projected scale of UAS/UAM operations is so large that there will be a significant need for congestion mitigation through UTM. The scale of operations will also magnify the impact of any unfairness in the allocations, which could affect thousands of aircraft every hour.

B. Conventional Implementation of ATFM

Certain features of conventional aviation make ATFM easier to implement in practice. It is worth highlighting them and comparing them to the case of UTM. Firstly, airport constraints are generally considered the primary bottlenecks and are prioritized over airspace flow constraints. However, for UAS operations, parts of the airspace may be more congested than vertiports, which are easier to build and operate than airports. Fairness has not been considered in detail in the context of networked airspace resources. Secondly, there is little unscheduled or pop-up demand with commercial aviation, and schedules are generally known months in advance. By contrast, UTM demand is expected to be dynamic and unscheduled, with low lead times in flight plan filings.

C. Addressing UTMF challenges

We address these challenges by (a) comparing multiple metrics of fairness (overtakings, number of reversals, and time-ordered-deviation) and evaluating the performance of one metric when the system is optimized for another; (b) leveraging an industry-developed UAS/UAM traffic simulator for the dynamic demand and trajectories; and (c) implementing UTMF in a receding horizon manner to account for dynamic demand and low file-ahead times.

III. THE TRAFFIC FLOW MANAGEMENT PROBLEM (TFMP)

In this section, we present the main formulation for the traffic flow management problem. We describe three metrics to measure fairness and show how they can be incorporated in the optimization. The initial formulation is the classical ATFM formulation presented in [6].

A. Setup and Notations

Consider time to be discretized, with each time interval of length ΔT , and the set of all time periods $\mathcal{T} = \{1, \dots, T\}$. The set of all airports is \mathcal{A} , and the set of all airspace sectors is \mathcal{S} . The capacity of each airport $a \in \mathcal{A}$ and sector $s \in \mathcal{S}$ for every time period $t \in T$ is denoted by $c_{a,t}$ and $c_{s,t}$ respectively. Associated with every flight $f \in \mathcal{F}$ is a schedule departure time d_f , origin airport $orig_f$, scheduled arrival time a_f , destination airport $dest_f$, and a list of sectors that it must fly through \mathcal{S}^f . Each flight has a path that begins at an airport, traverses multiple sectors, and ends at an airport. Moreover, each flight has a set of times T_j^f that it can arrive at sector or airport j . Each sector s has a capacity at time t , $C(s,t)$.

\mathcal{T} : Set of time periods $\{1, \dots, T\}$ of length ΔT

\mathcal{A} : Set of all airports

\mathcal{S} : Set of all airspace sectors

\mathcal{F} : Set of all flights

$C(s,t)$: 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 scheduled

\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 $j \in \mathcal{S} \cup \mathcal{A}$ (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

B. Baseline TFMP

The objective function minimizes total delay cost (TDC). The expression for total delay cost (TDC) is $TDC = GD + \alpha AD$, where total delay (TD) includes ground delay (GD) and airborne delay (AD) and α is the ratio of airborne delay cost to ground delay cost. The expression can be manipulated as follows: $TDC = GD + \alpha AD = GD + \alpha(TD - GD) = \alpha TD - (\alpha - 1)GD$. Below, the costs of total delay and ground delay are super-linear to favor evenly-distributed delays.

$$c_{total}^f(t) = \alpha(t - a^f)^{1+\epsilon} \quad (1)$$

$$c_g^f(t) = (\alpha - 1)(t - d^f)^{1+\epsilon} \quad (2)$$

$$TDC = \sum_{f \in \mathcal{F}} \left(\sum_{t \in T_{dest_f}^f} c_{total}^f(t) (w_{dest_f,t}^f - w_{dest_f,t-1}^f) - \sum_{t \in T_{orig_f}^f} c_g^f(t) (w_{orig_f,t}^f - w_{orig_f,t-1}^f) \right) \quad (3)$$

The following constraints must be satisfied:

$$\sum_{f \in \mathcal{F}: orig_f=k} (w_{k,t}^f - w_{k,t-1}^f) \leq D(k,t), \forall k \in \mathcal{A}, t \in \mathcal{T} \quad (4a)$$

$$\sum_{f \in \mathcal{F}: dest_f=k} (w_{k,t}^f - w_{k,t-1}^f) \leq A(k,t), \forall k \in \mathcal{A}, t \in \mathcal{T} \quad (4b)$$

$$\sum_{f \in \mathcal{F}: i \in \mathcal{S}^f, j = \mathcal{S}_i^f} (w_{i,t}^f - w_{j,t-1}^f) \leq C(j,t), \forall t \in \mathcal{T} \quad (4c)$$

$$w_{i,t}^f = 0, \forall f \in \mathcal{F}, t = \underline{T}_j^f - 1, i = \mathcal{S} \cup \mathcal{A} \quad (4d)$$

$$w_{i,t}^f = 1, \forall f \in \mathcal{F}, t = \bar{T}_j^f, i = \mathcal{S} \cup \mathcal{A} \quad (4e)$$

$$w_{i,t}^f - w_{j,t-l_{f,j}}^f \leq 0, \forall f \in \mathcal{F}, t \in T_i^f, i \in \mathcal{S}^f : i \neq orig_f, j = \mathcal{P}_i^f \quad (4f)$$

$$w_{i,t-1}^f - w_{i,t}^f \leq 0 \forall f \in \mathcal{F}, i \in \mathcal{S}^f, t \in T_i^f \quad (4g)$$

$$w_{i,t}^f \in \{0, 1\} \forall f \in \mathcal{F}, i \in \mathcal{S}^f, t \in T_i^f \quad (4h)$$

The key aspect of the formulation that lends computational tractability to larger scale problems is the choice of the decision variable $w_{i,t}^f$, which is a binary variable that is non-decreasing in time (Constraints (4g) and (4h)). $w_{i,t}^f$ is 1 if flight f has arrived at resource i by—but not necessarily at—time t . Thus, a flight f is said to enter a resource i (which could be an airport or a sector) at time t if $(w_{i,t}^f - w_{i,t-1}^f) = 1$. Constraints (4a), (4b), and (4c) enforce departure, arrival, and sector capacities, respectively. Constraint (4d) ensures that a flight does not reach a sector before the earliest feasible time. Analogously, constraint (4e) 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 (4f).

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 and overtaking* [9]: 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. More precisely, a flip in the ordering of flight arrivals at a sector or an airport with respect to the original schedule is called as a *reversal*, and the magnitude of the reversal, in terms of the difference in arrival times is referred to as *overtaking*.

Two additional sets for reversals and overtaking 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
- λ_r : Penalty factor for reversals
- λ_o : Penalty factor for overtaking

For reversals, 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. In the objective function, we sum the previously defined TDC with the total number of reversals multiplied by a weight λ_r .

$$\min TDC + \lambda_r \sum_{j \in S, (f,f') \in R^j} s_{f,f',j} \quad (5)$$

The following constraint must be satisfied:

$$s_{f,f',j} = \max(0, w_{j,t}^{f'} - w_{j,t}^f) \quad \forall t \in T_{f,f',j}^r \quad (6)$$

For overtaking, we define a new variable $s_{f,f',j}^i$ which is 1 if flight f' arrives but flight f does not arrive by time $\underline{T}_j^f + i$ in resource j , where f was scheduled to arrive before f' , and 0 otherwise. The objective function looks similar to incorporating reversals, but note that $s_{f,f',j}^i$ is summed over the cardinality of $T_{f,f',j}^r$.

$$\min TDC + \lambda_o \sum_{j \in S, (f,f') \in R^j} |T_{f,f',j}^r| s_{f,f',j}^i \quad (7)$$

The following constraint must be satisfied:

$$s_{f,f',j}^i = \max(0, w_{j,\underline{T}_j^f+i}^{f'} - w_{j,\underline{T}_j^f+i}^f) \quad (8)$$

2) *Time-order deviation* [10]: 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 first-come first-serve, 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
- $c_{TODA}^f(t)$: Additional delay cost when flight f is delayed for time t
- λ_t : Penalty factor for time-order deviation

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

$$d_f^{FCFS} \triangleq \max_{i \in \mathcal{S} \cup \mathcal{A}} FCFS_i^f \quad (9)$$

Thus, the modified optimization problem is

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

$$\text{where } c_{TODA}^f(t) = (\max\{0, t - a_f - d_f^{FCFS}\})^{1+\epsilon}. \quad (10)$$

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 [17]. The vertiport traffic is determined through 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. 1 shows the scenario with 50 flights/hour.

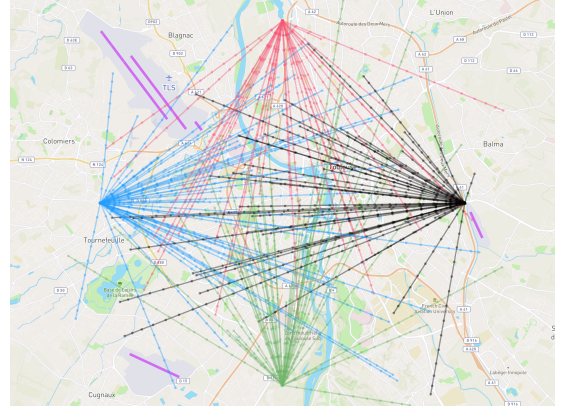


Fig. 1: Simulation map with 4 vertiports.

One of the key requirements of the TFMP formulation is that time is discretized into timesteps. We rounded sector entry and exit times to the nearest 60 s, while ensuring that each flight spent at least one timestep in each sector. We set a sector time discretization threshold of 3 s, and omit a sector from a flight's trajectory if it spent less than 3 s in it. Also, the TFMP formulation requires that a flight may only traverse through a

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	$\alpha = 3$

sector once. We smoothed the trajectory in 8 instances where a flight entered a sector multiple times. For example, a flight that entered sector A, briefly left to sector B, then reentered sector A would be modified to stay in sector A.

An additional factor that we accounted for was maximum battery life, which we assumed to be 20 min. We used the remaining battery life and the unimpeded time-to-destination to calculate an upper-bound on airborne delay for each flight at each sector. Table I lists some additional parameters used for the experiment.

B. Fairness-Efficiency Tradeoff

We seek to evaluate the fairness-efficiency tradeoff when incorporating one of three fairness metrics: reversals, overtaking, or time-order deviation. Recall that the weight that a fairness metric is given is represented by λ_r , λ_o , or λ_t . We vary these values to generate fairness-efficiency curves. We use total delay cost as a measure of efficiency (refer to equation (3)). Note that total delay cost is distinct from total delay, as it penalizes airborne delay 3 times more than ground delay.

C. Rolling Horizon Implementation

The standard TFMP 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 TFMP. With a rolling horizon of length n minutes long, we propose to solve the TFMP once for every horizon (i.e. every n minutes). Each flight is thus scheduled to takeoff in one horizon and must file their flight plan before the start of the horizon. Once a flight is assigned a revised schedule, it is fixed and acts as a constraint for flights in the next step. For example, if $n = 5$ mins., we solve the TFMP at 6:00, 6:05, 6:10, and so on. All flights departing between 6:05 and 6:10, regardless of intended flight duration, 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 horizons. To enable greater flexibility, while planning flights for a time horizon, one may also reconsider any previously scheduled flights; we are currently exploring this implementation.

V. RESULTS

A. Fairness-Efficiency Tradeoffs

Incorporating fairness metrics in the objective function results in an inherent tradeoff between fairness and efficiency, measured in terms of the total delay cost. In the baseline formulation, there is no fairness consideration, and the objective function is simply the total delay cost. Thus, when incorporating fairness metrics in the objective function, the total delay cost either remains the same or increases as the additional terms drive the solution away from the optimal delay cost. In return, we expect fairness to increase. Additionally, we want to evaluate the effect of incorporating one fairness metric in the objective on other fairness metrics.

Fig. 2 shows the average number of reversals per flight and the total delay cost when minimizing total delay cost for various scenarios. The ‘Baseline’ case minimizes the total delay cost, and the other three cases (‘Reversal’, ‘Overtaking’, ‘TODA’) incorporate one of the three fairness metrics. 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 for the baseline case, but several data points for reversals, overtaking, and TODA, corresponding to different λ_r , λ_o , and λ_t values, respectively.

We first look at the results of incorporating reversals as a fairness metric in the low demand scenario (shown as blue hexagon points). As λ_r increases, the number of reversals decreases and the total delay cost increases relative to baseline (shown as a black square). For small λ_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 λ_r , 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 a flight can endure, the number of reversals could be driven to zero at the cost of very high total delay.

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 λ_r , the average number of reversals approaches zero while average total delay cost increases substantially.

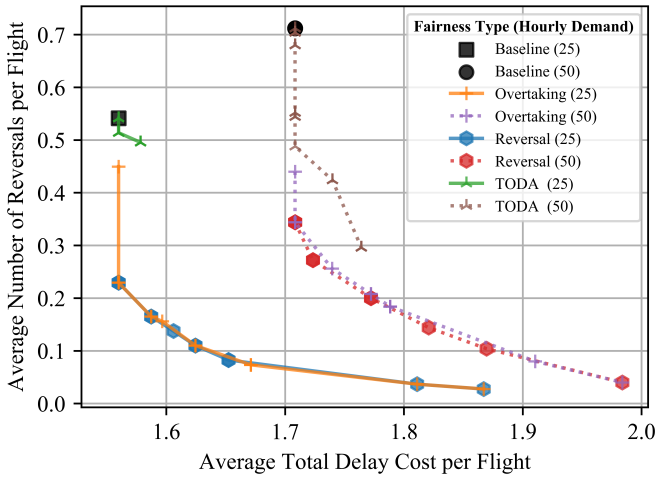


Fig. 2: Reversals vs. Total Delay Cost (TDC) when incorporating different fairness metrics. The hourly demand level is shown in parentheses.

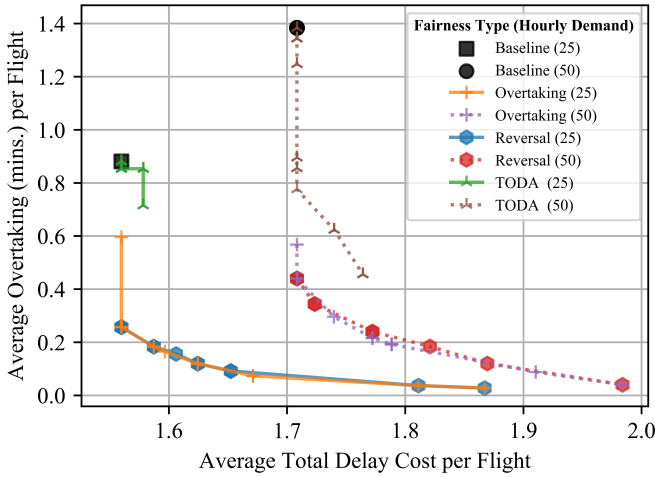


Fig. 3: Overtaking vs. Total Delay Cost (TDC).

Incorporating overtaking produces nearly identical results as when incorporating reversals. In many cases they have identical optimal solutions, not only with regard to fairness and efficiency, but also concerning schedule and delay allocation. This is expected since the two fairness metrics are intertwined, with overtaking measuring the magnitude of time duration that a given pair of flights was reversed. Whereas reversals and overtaking are nearly in lockstep, time-order deviation behaves differently from reversals or overtaking. For small λ_r , 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 incor-

porating reversals. For larger λ_r , the optimal solution does not change and no further reductions in reversals are apparent.

Fig. 3 is similar to Fig. 2 but displays average overtaking (in minutes) instead of the number of reversals on the y-axis. Since reversals and overtaking are closely related, it comes as no surprise that the efficiency-fairness tradeoff of both are similar. Average overtaking decreases exponentially in relation to the total delay cost, and for very large λ_r or λ_o , it is possible to reduce overtaking to zero, albeit at a great expense to the total delay cost. Incorporating time-order deviation impacts overtaking similarly to the way it impacted reversals.

Fig. 4 shows the average time-order deviation (in minutes) on the y-axis. We first consider how incorporating time-order deviation in the objective affects the average time-order deviation per flight. As λ_r increases, the average time-order deviation decreases and the average total delay cost increases. The decreases in time-order deviation are modest, but more pronounced in the high demand scenario, for which the tradeoff between the average time-order deviation and the average total delay cost is linear. At $\lambda_r = 2$, the average time-order deviation decreases by 4.5% and the total delay cost increases by 3%. The increase in total delay cost happens despite a reduction in total delay (from 208 min in the baseline to 201 min)—this is because the airborne delay (which is 3x more costly than ground delay) increases.

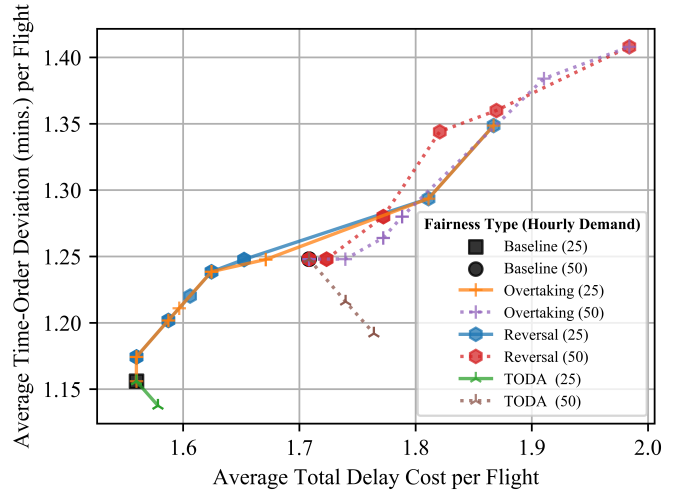


Fig. 4: Time-Order Deviation vs. Total Delay Cost (TDC).

While penalizing reversals or overtaking can drive its value to zero, it is not possible to drive the average time-order deviation to zero, no matter how large λ_r gets. This is inherent to the way time-order deviation is defined (10). If all flights have delay assigned greater than or equal to their maximum expected delay, time-order deviation cannot be reduced by reallocating delay to flights that have delay assigned less than their maximum expected delay. Instead, time-order deviation

can only be decreased by also decreasing total delay. Thus, when all flights have delay assigned that is greater than or equal to their maximum expected delay and the total delay has been minimized, then the time-order deviation is also minimized. This appears to be the case here, as minimizing 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 $\lambda_t = 2$. Incorporating reversals or overtaking results in a 17% increase in average time-order deviation in the low demand scenario and a 13% increase in the high demand scenario. In contrast, incorporating time-order deviation can slightly decrease reversals or overtaking.

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 λ_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. Further, incorporating time-order deviation bounds the loss in efficiency while remaining robust to the choice of λ_t . These observations suggest that time-order deviation may be a suitable fairness metric in practice.

B. 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. 5, 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. The rolling horizon concept works for flights of any intended duration, but it does require that flights file their flight plan before the start of the horizon. Only the results of incorporating reversals or time-order deviation are shown, as overtaking behaves very similarly to reversals. Note that fairness is only incorporated among the flights that are planned in a given horizon.

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 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 close to a linear decrease. Incorporating time-order deviation generally increases the number of reversal. 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.

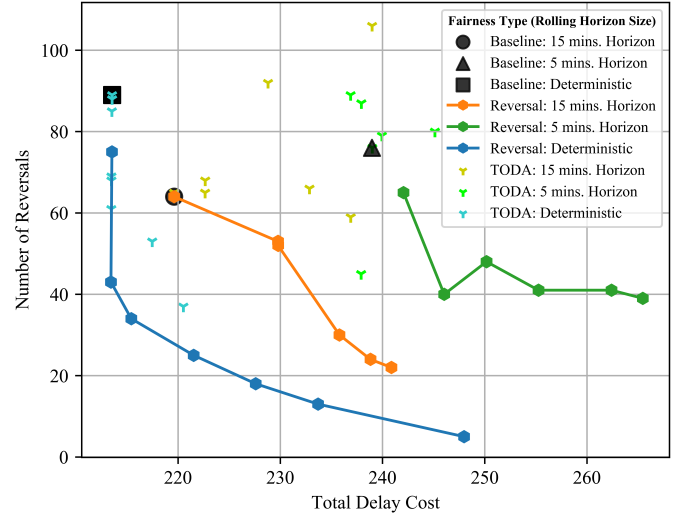


Fig. 5: Reversals vs. Total Delay Cost (TDC), by length of rolling horizon.

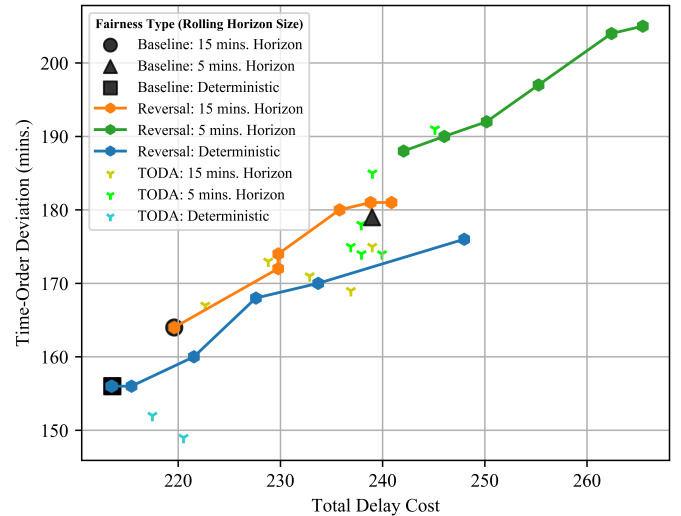


Fig. 6: Time-Order Deviation vs. Total Delay Cost (TDC), by length of rolling horizon.

Fig. 6 is similar to Fig. 5, except it shows time-order deviation rather than the number of reversals on the y-axis. We observe that decreasing the length of the planning horizon (from deterministic to 15 minutes to 5 minutes) increases the total delay cost and the time-order deviation. This is in contrast to the trend with reversals, which decreased when using a rolling horizon, relative to baseline. Additionally, we note that in the rolling horizon case incorporating reversals increases the time-order deviation, similar to the deterministic case. The impact of incorporating time-order deviation is unclear. For the 15 and 5-minute horizons, incorporating time-order deviation did not always improve time-order deviation. In fact, sometimes it increased time-order deviation, highlighting that a ‘greedy’ approach in every horizon may not lead to optimal outcomes in the longer term.

VI. CONCLUSIONS

This paper explores incorporating fairness metrics in UTM. Before deciding the extent to which fairness is implemented, it is important to choose a metric that defines fairness. From our analysis, time-order deviation appears to be a promising metric for fairness as it is robust to the specific choice of the λ penalty, strives for equality in a relative sense rather than on an absolute scale, and does not significantly compromise efficiency. However, it is also worth remembering that a significant fraction of the improvements in fairness and reversals can be obtained for a small penalty in delays if the appropriate λ is chosen. The UTFM framework can be used to evaluate the centralized efficiency and fairness of any trajectory set (e.g., trajectories with different demand profiles or ‘geofenced’ airspace restrictions).

Given the diversity of potential users of UTM, an area of ongoing work is incorporating operator preferences into the UTFM formulation. Operator preferences of several types need to be studied ranging from the objective functions, preferred choice of fairness metric, the extent of fairness desired, air hold to ground hold cost ratio, and the maximum acceptable delay. Presently, we are performing experiments to address the following questions: (a) How does adding fairness preferences for one set of vehicles change the fairness metrics for other vehicles (a measure of the externality on the system); and (b) are aligned fairness preferences (i.e., the same choice of fairness metric) of different operators better for individual operators than the scenario in which operators differ in their fairness preferences.

Finally, we believe there is significant scope for future work with respect to the rolling horizon implementation of UTFM. One potential extension would allow the re-planning of airborne flights that have already been scheduled. In the extreme case, the rolling horizon could be implemented such that each flight is scheduled on-demand.

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