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× increase in the number of flights due to UAS operations, and a 30× 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 takeoff/landing zones (vertiports), and to improve system efficiency.

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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 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 by predicting the usage of various airspace and airport resources, along with 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 f₁ arrives at a resource before another flight f₂, which was originally scheduled to arrive at that resource before f₁. 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. 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 broadly recognized as a key consideration by industry
stakeholders as well as 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 (for instance 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. An algorithm that ensures a certain degree of fairness is then 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 fairness to various degrees? Are certain metrics of fairness better 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 or 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 the UTM context.

Our major findings are as follows:

1) Depending on the fairness metric, a significant increase 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. 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 may increase or decrease, 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 UTFM

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, with short file-ahead times. It is therefore difficult to anticipate the usage of airspace and vertiport resources. Consequently, proactive measures such as takeoff holds cannot be assigned reliably and accurately. 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 an hour.

B. Conventional ATFM applications

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 or business trajectory filings.
C. Addressing UTFM 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 UTFM 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 [6].

A. Setup and notations

Consider time to be discretized, with each time interval of length $\Delta t$, and the set of all time periods $\mathcal{T} = \{1, \ldots, T\}$. 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 $c_{at}$ and $c_{st}$ respectively. Associated with every flight $f \in \mathcal{F}$ is a schedule departure time $d_{f}$, departure airport $dep_{f}$, scheduled arrival time $a_{f}$, destination airport $orig_{f}$, and a list of sectors that it must fly through $\mathcal{F}_f$. 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 $T_f^i$ that it can arrive at sector or airport $j$. Each sector $s$ has a capacity at time $t$, $C(s, t)$. 

- $\mathcal{F}$: Set of time periods $\{1, \ldots, T\}$ of length $\Delta T$  
- $\mathcal{A}$: 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 $t$  
- $d_{f}$: Scheduled departure time for flight $f \in \mathcal{F}$  
- $a_{f}$: Scheduled arrival time for flight $f \in \mathcal{F}$  
- $\mathcal{F}_f$: Sequence of sectors in flight $f$’s scheduled trajectory  
- $\mathcal{F}_f^j$: Next sector after $j$ in flight $f$’s trajectory  
- $\mathcal{F}_f^j$: 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  
- $T_f$: Set of feasible time periods for flight $f$ to arrive at resource $j \in \mathcal{A} \cup \mathcal{S}$ (airport or sector)  
- $\mathcal{F}_f^j$: Latest time in the set $T_f^j$  
- $\mathcal{T}_f^j$: Earliest time in the set $T_f^j$

B. Baseline TFMP

The objective function for the baseline TFMP is to minimize total delay cost ($TDC$), which consists of two terms: the total delay (TD), and the cost reduction with incurring ground delay (GD) rather than airborne delay (AD). The expression for $TDC$ comes from $AD = TD - GD$ and $TD = GD + \alpha AD = \alpha TD - (\alpha - 1)GD$. The costs of total delay and ground delay are super-linear to favor evenly-distributed delays.

\[
\begin{align*}
TDC &= \sum_{f \in \mathcal{F}} \left( \sum_{t \in T_{dest_{f}}} c_{total}(t)(w_{dest_{f}, t} - w_{dest_{f}, t-1}) - \sum_{t \in T_{dest_{f}}} c_{g}(t)(w_{orig_{f}, t} - w_{orig_{f}, t-1}) \right) 
\end{align*}
\]

The following constraints must be satisfied:

\[
\begin{align*}
\sum_{f \in \mathcal{F}, \mathcal{T}_{f} \subseteq \mathcal{S}} (w_{f, k_{i}} - w_{f, k_{i-1}}) &\leq D(k,t), \forall k \in \mathcal{A}, t \in \mathcal{T} \\
\sum_{f \in \mathcal{F}, \mathcal{T}_{f} \subseteq \mathcal{S}} (w_{f, k_{j}} - w_{f, k_{j-1}}) &\leq A(k,t), \forall k \in \mathcal{A}, t \in \mathcal{T} \\
\sum_{f \in \mathcal{F}, \mathcal{T}_{f} \subseteq \mathcal{S}} (w_{f, i} - w_{f, j_{f}}) &\leq C(j, t), \forall j \in \mathcal{S}, t \in \mathcal{T} \\
\end{align*}
\]

The key aspect of the formulation that lends computational tractability to larger scale problems is the choice of the decision variable $w_{i, f}$, which is a binary variable that is non-decreasing in time (Constraints (4g) and (4h)). $w_{i, f}$ 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 ($\mathcal{F}_{f}^{i} - \mathcal{F}_{f}^{i-1}$) = 1. Constraints (4a), (4b), and (4c) enforce departure, arrival, and sector capacities, respectively. Constraint (4d) ensures that a flight does not take off earlier than planned, or reach a sector before the earliest feasible time. Analogously, constraint (4e) enforces that a flight must have departed, or arrived 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 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.

\[ R^f \] : Pairs of reversible flights

\[ T^r_{f,f',j} \] : Set of time periods common for flights \( f \) and \( f' \) where a reversal could occur at resource \( j \)

\( \lambda_r \) : Penalty factor for reversals

\( \lambda_o \) : 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 \( \lambda_r \).

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

The following constraint must be satisfied:

\[
s_{f,f',j} = \max(0, w^f_{j,i} - w^f_{j,i+1}) \forall t \in T^r_{f,f',j} \tag{6}
\]

For overtaking, we define a new variable \( s^o_{f,f',j} \) which is 1 if flight \( f' \) arrives after flight \( f \) does not arrive by time \( i \) 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 \( s^o_{f,f',j} \) is summed over the cardinality of \( T^o_{f,f',j} \).

\[
\min \ TDC + \lambda_o \sum_{j \in S, (f,f') \in R^o} s^o_{f,f',j} \tag{7}
\]

The following constraint must be satisfied:

\[
s^o_{f,f',j} = \max(0, w^f_{j,i+1} - w^f_{j,i}) \tag{8}
\]

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

\[
d^f_{FCFS} : \text{Maximum FCFS delay for flight } f
\]

\[
c^f_{TODA}(t) : \text{Additional delay cost when flight } f \text{ is delayed for time } t
\]

\[
\lambda_o : \text{Penalty factor for time-order deviation}
\]

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

\[
d^f_{FCFS} = \max_{i \in \mathcal{F} \cup \mathcal{S}} FCFS^f_i \tag{9}
\]

Thus, the modified optimization problem is

\[
\min \ TDC + \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{A}_f} c^f_{TODA}(t)(w^f_{\text{dest},f} - w^f_{\text{dest},d,t-1}),
\]

where

\[
c^f_{TODA}(t) = (\max(0, t - a^f - d^f_{FCFS}))^{1+\varepsilon}. \tag{10}
\]

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 skip a sector if a flight spent less than 3 s in it. Another requirement of the TFMP 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.

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 $\lambda_r$, $\lambda_o$, or $\lambda_t$. We vary these values to generate fairness-efficiency curves. We use total delay cost as the efficiency metric, as shown in (3). Note that total delay cost is distinct from 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 $\lambda_r$, $\lambda_o$, and $\lambda_t$ 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 $\lambda_r$ increases, the number of reversals decreases and the total delay cost increases relative to baseline (shown as a black square). 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 $\lambda_r$, 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

\[ \text{TABLE I} \]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timestep Size</td>
<td>60 s</td>
</tr>
<tr>
<td>Sector X-Y Dimensions</td>
<td>1 km × 1 km</td>
</tr>
<tr>
<td>Sector Z Dimension (Height)</td>
<td>65 m</td>
</tr>
<tr>
<td>Sector Capacity</td>
<td>1 per sector</td>
</tr>
<tr>
<td>Departure Capacity</td>
<td>2 per timestep</td>
</tr>
<tr>
<td>Sector Discretization Threshold</td>
<td>3 s</td>
</tr>
<tr>
<td>Maximum Battery Life</td>
<td>20 min.</td>
</tr>
<tr>
<td>Airborne Delay Cost to Ground Delay Cost Ratio</td>
<td>$\alpha = 3$</td>
</tr>
</tbody>
</table>
a similar shape, and for very high $\lambda_r$, the average number of reversals approaches zero while average total delay cost increases substantially.

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 $\lambda_t$, 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.

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 $\lambda_r$ or $\lambda_o$, 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 $\lambda_t$ 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 $\lambda_t = 2$, 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.
be accompanied by decreases in 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 $\lambda_{t}$ 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. Further, incorporating time-order deviation bounds the loss in efficiency while remaining robust to the choice of $\lambda_{t}$. 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. 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.](image)

![Fig. 6: Time-Order Deviation vs. Total Delay Cost (TDC), by length of rolling horizon.](image)
obtained for a small penalty in delays if the appropriate $\lambda$ fraction of the improvements in fairness and reversals can be efficient. However, it is also worth remembering that a significant metric for fairness as it is robust to the specific choice of the operator preferences. For example, 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 $\lambda$ 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 $\lambda$ is chosen.

An area of ongoing work is incorporating operator preferences in the TFMP 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) Is having aligned fairness preferences (same choice of fairness metric) for different operators better for individual operators than the case where operators have different fairness preferences.

Finally, we believe there is significant scope for future work in extending the rolling horizon implementation of the TFMP. One extension would allow the re-planning of flights in the air that have already been scheduled. In the extreme case, the rolling horizon could be implemented such that each flight is scheduled at the time of request, in the order in which the demand appears.

REFERENCES