Strategic Demand Management in U-Space with RTTA Controls

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This paper investigates the demand and capacity management in very low level urban airspace, using the notion of Reasonable Time to Act (RTTA) from the European Concept of Operations for U-space (CORUS) and its Urban Air Mobility (UAM) extension (CORUS-XUAM). We develop methodology for determining optimal RTTA values which balance early airspace reservation versus the flexibility of last-minute adjustments. Our analysis addresses the trade-offs between early deconfliction (which may lead to inefficient airspace use due to unnecessary reservations), and late deconfliction (which implies reduced predictability for uncrewed aerial systems operators). We incorporate weather uncertainties, using simulations to quantify the impact of varying RTTA lengths on airspace congestion and delay costs.

I. Introduction

Demand and Capacity Balancing (DCB) and strategic Conflict Resolution (CR) are at the heart of managing traffic of unmanned (a.k.a. uncrewed) aerial systems (UAS) a.k.a. drones. A fundamental question in UAS traffic management (UTM) is when to do the strategic deconfliction of U-plans (a U-plan [1] is a UTM counterpart of the flightplan in conventional aviation). EASA's acceptable means of compliance (AMC) and guidance material (GM) [2, GM7 Art 3(4)] to EU's U-space Regulation 664 [3] allows local authorities to define a time window during which flight activation may be requested, as well as to limit how long before the takeoff the flight authorization may be sought. These measures are envisioned to augment First Come First Serve (FCFS) DCB and CR (complying to the U-space regulations), making them more efficient and fair to airspace users. The European ConOps for the U-space, CORUS [4], and its Urban Air Mobility (UAM) extension CORUS-XUAM [1] suggest that instead of FCFS, U-plans may be deconflicted at a certain time before the start of the flight: the length of this time interval between the deconfliction and the flight start was dubbed RTTA (Reasonable Time to Act, sometimes expanded as Required Time to Act).

Despite the interest in RTTA (due to its critical role in UTM) both in the EU and the US [5, 6], there exist no guidelines on deciding how long the RTTA should be, which motivates further research on the topic. The challenge lies in striking an optimal balance between the following two conflicting considerations:

- Deconflicting early (e.g., on an FCFS basis, as the U-plans arrive) may be suboptimal because when flight plans that request departure at a later time are scheduled first, it creates gaps between them which may be insufficient for other (later-filed) operations, leading to less efficient use of airspace. This strategy is also sensitive to uncertainty, for example, cancellations: by the time of the flight, the operator may decide to cancel the flight, leaving the reserved airspace unused. (Early airspace reservations are also unfair to operators who do not know their plans well in advance, e.g., various kinds of rapid response missions, on-demand services like delivery, etc.)
- Deconflicting close to the actual flight discourages early planning, and may disappoint an operator whose plan is rejected by the U-space Service Provider (USSP) close to the time when the operation is about to start (thus not giving the operator a reasonable time to act upon the U-plan rejection).

The overall idea with RTTA is that a U-plan that is past RTTA is "frozen," i.e., it will not be changed (unless it will conflict with a priority flight like an emergency medical service or police). That is, at RTTA, the USSP promises that

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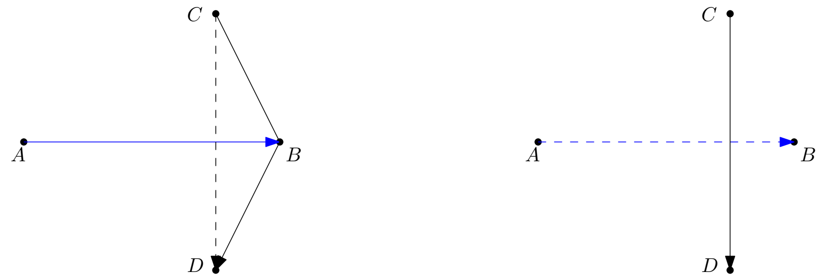

Fig. 1 Right: At 1000, Operator 1 submits the plan to fly $A \rightarrow B$ at 1200; the RTTA is 1 hour, so the plan is approved at 1100. At 1140, Operator 2 submits a plan to fly $C \rightarrow D$ at 1155; because the plan conflicts with an already approved flight, the plan is modified to fly around B (alternatively, the flight would be delayed). Left: At 1145, Operator 1 cancels its flight. If RTTA were shorter (e.g., 5 minutes vs. 1 hour), the first flight would not need to be approved, and the second flight could go direct from C to D.

the flight may be executed as planned assuming nominal operating conditions. On the contrary, a flight that has not reached its RTTA may still be rejected by the USSP, e.g., because it conflicts with another flight, and a modification of the U-plan may be suggested.

Naturally, it is better for the drone operator to have its U-plan approved sooner rather than later: The approval assures that the operation will happen as planned because the airspace for the flight is reserved. On the contrary, the USSP would want to deconflict the flight as close to the start of the operation as possible because then the USSP has better situational awareness: more information is available regarding the other (potentially conflicting) U-plans, the airspace capacity is better known, the weather forecast uncertainty decreases with the time (we emphasize that the issue regarding weather is particularly salient: for urban use cases, it is very difficult to have accurate urban microweather prediction services; for rural/regional air mobility use cases, we will still need more granular en route weather predictions than what we currently have today), and so on. In particular, the USSP may not want to commit to an early reservation of the airspace for the operator simply because the flight may be canceled or delayed (due to a variety of reasons, e.g., drone not being ready to fly, dynamically changing demands, etc.). This leads to revenue loss, as another U-plan might have been *overly-conservatively* rejected (or modified to fly around, which increases the operating cost) due to a (no longer relevant) conflict with the to-be canceled flight (see Figure 1 for a synthetic example). Even in the absence of cancellations, scheduling of flights with later departure time first may lead to inefficient use of airspace, because other flights need to be fitted between them, which is not always possible (a synthetic example is presented in Figure 2).

One of our main insights, to be explored in this paper, is that above-described conflicting objectives are reminiscent of well-known problems in airlines revenue management:

- *Seat reservation.* In its simplest form, the problem is to decide how many seats on an airplane should be reserved for the demand stream of high-paying business passengers: Assuming that leisure passengers book early, and high-yield business passengers book later in the process, airline revenue management seeks to protect enough seats for late-arriving business passengers, while opening enough seats for low-yield, leisure passengers to fill up the aircraft. Analogously, a USSP may delay a "leisure" U-plan (an operation, like inspection, which is scheduled in advance and can tolerate delays) to leave room in the airspace in anticipation of a "business" U-plan (an on-demand operation like delivery or air taxi, with low delay tolerance).
- *Overbooking.* Airlines sell more tickets for a flight than the capacity of the airplane, under the assumption (driven by historical no-show rate data) that some passengers will not show up for various reasons. Analogously, a USSP may accept more airspace reservations than the airspace capacity allows because the demand is quite dynamic and the U-plan cancellation rates are known (from historical data or models).

Roadmap

The next section gives the background and surveys the related work, including details of the well studied models for addressing seat reservation and overbooking. Section III focuses the tradeoffs between RTTA and delays in drone traffic, and Section IV quantifies the impact of weather on RTTA. We conclude in Section V outlining some directions for future research.

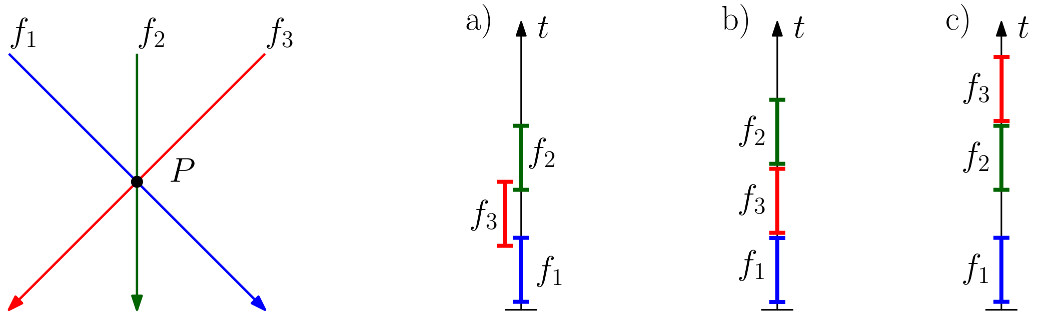

Fig. 2 Left: Operators submit 3 requests to fly f_1, f_2, and f_3 (in that order), that pass through the common point P. All three requests specify the earliest possible time of departure (which is also the desired time). Right: Gantt charts of the occupancy of P by the three U-plans. The vertical axis represents the timeline, and the time periods when P is occupied by U-plans are represented by the three bold line segments. When scheduled at the preferred time of departure without any deconfliction (a), there is a conflict between f_3 and the other two flightplans. If RTTA is very low (b), i.e., the system deconflicts flights in the order of their preferred departure time, f_3 would be scheduled directly after f_1, and all three plans would be finely packed. However, if RTTA is high (c) and the system deconflicts flights in the order in which the requests arrive (FCFS), the system would schedule f_2 after f_1 (because request for f_2 arrived before f_3) at the earliest possible departure time, which creates a gap between f_1 and f_2 in which f_3 cannot be fitted.

II. Background and related work

CORUS-XUAM ConOps [1] identifies RTTA with the Pre-Tactical phase (Fig. 3); however, in many other places (e.g., in Section 2.2.2.3.3.1 introducing RTTA for the first time) the ConOps gives a more reasonable definition that RTTA is a single moment in time when the USSP checks whether the submitted U-plan can be executed as planned or should be modified (e.g., to avoid conflicts). The question is how far in advance of the flight that moment should be. Additionally, better understanding how RTTA can be used for strategic demand management has the potential to help inform the Cooperative Operating Practices (COPs) currently being developed as a part of the US Federal Aviation Adminstration (FAA)'s UAM Concept of Operations. Such COPs are expected to take the form of industry-defined (e.g., UAS fleet operators), regulator-approved practices that inform aspects such as airspace usage equity and demand-capacity balance [7].

Understanding the optimal look-ahead (or look-back) time (or distance) is a fundamental ATM question. For instance, it would be hard to handle traffic in Terminal Maneuvering Areas (TMAs) if the aircraft were appearing unexpectedly on a short notice. Extending the planning-horizon to sequence the aircraft 100-200 nmi before the TMA (e.g., using the SESAR's solution Extended Arrival Management E-AMAN [8] or the Extended Metering function of US FAA's Time-Based Flow Management tool) leads to more efficient, smooth, and organized traffic management. In the limit, as the planning horizon goes further and further back from the TMA, one would deal with the full gate-to-gate trajectory (arriving at ideas like Trajectory-Based Operations TBO [9] and Ground Delay Programs [10] keeping the aircraft from flying until the capacity constraints are alleviated). However, with a longer lead time, the uncertainty of the situation increases, which complicates traffic flow management. Striking the correct middle ground by finding the right distance/time to look back, when the uncertainty is sufficiently low (so predictability is good) while there is still time to act/change the course of action without high cost, is an area of active research. Finding the right value for RTTA looks to be an analogous challenge: to address it, one needs to see how multiple KPIs (delays, fairness, safety, etc.) depend on RTTA in various scenarios. In this paper, we make one of the initial steps in this direction (building, in particular, on work in [5] who explored fairness on two synthetic examples; here, we use a more realistic scenario of simulated urban traffic).

Airline revenue management

A minimal non-trivial seat reservation problem may be formulated as follows: An airline operates a plane with 100 seats. Let r denote the revenue from selling an economy ticket (i.e., a ticket for a leisure passengers); assume that the price for the ticket is so low that all seats may be filled by the leisure passengers (for the total revenue of $100r$). Without loss of generality, assume that the revenue from selling a business ticket is 1. The number of business passengers

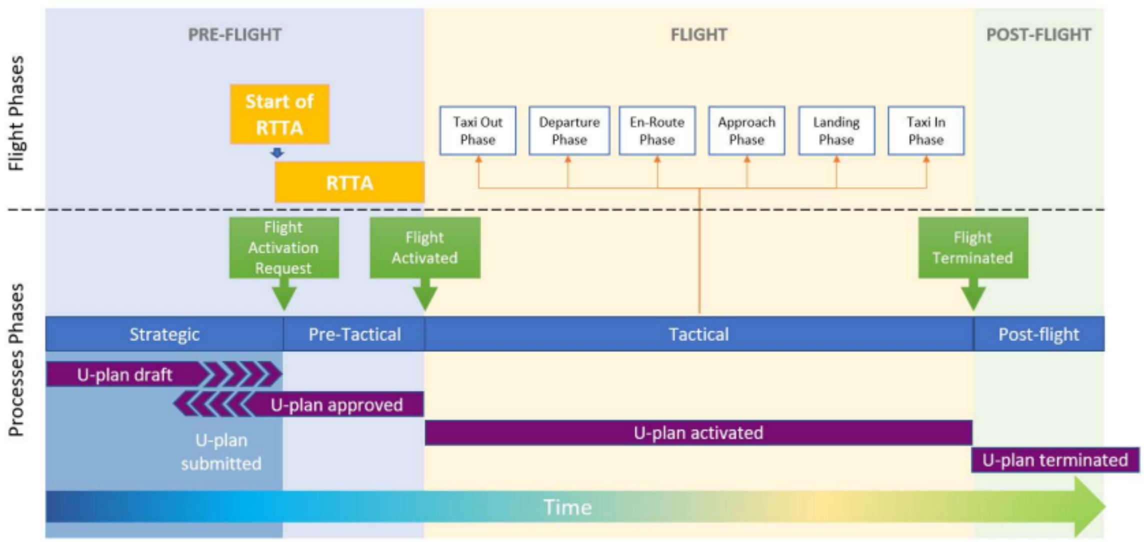

Figure 44: Visualisation of RTTA in U-plan and process phases timeline relation.

Fig. 3 Figure 44 from CORUS-XUAM ConOps [1]: RTTA in the life cycle of a U-plan.

who will want to buy the tickets is a random variable Y whose distribution $F(y) = \mathrm{P}\{Y \leq y\}$ is known from demand modeling (it may include historical data, surveys, etc. – how F is obtained is outside the scope of the problem). If x seats are reserved for business passengers, then the expected revenue from the flight is

$$E(x) \quad = \quad (100 - x)r \quad + \quad \sum_{y \leq x} y \cdot \mathrm{P}\{Y = y\} \quad + \quad x \cdot \mathrm{P}\{Y > x\}, \tag{1}$$

where the first term is the revenue from the leisure passengers, the second is the expected revenue from the business passengers if less than x of them buy tickets, and the third term is the revenue from the business passengers if $Y > x$ (weighted by the probability, $\mathrm{P}\{Y > x\} = 1 - F(x)$, of this event – since only x seats are reserved for the business, at most x business tickets can be sold). To differentiate (1) w.r.t. x, we assume that Y is a continuous random variable with differentiable cumulative distribution function (F) and approximate the second term with the integral $\int_{y>x} y f(y)\,\mathrm{d}y$ where $f = F'$ is the probability density function of Y:

$$E(x) \quad = \quad (100 - x)r \quad + \quad \int_{y>x} y f(y)\,\mathrm{d}y \quad + \quad x \cdot \mathrm{P}\{Y > x\}. \tag{2}$$

Then, the derivative is

$$E_x \quad = \quad -r \quad - \quad x f(x) \quad + \quad (1 - F(x)) + x f(x) \quad = \quad -r + 1 - F(x), \tag{3}$$

and the second derivative is

$$E_{xx} = -F'(x) \leq 0$$

because F is non-decreasing (as it is a valid cumulative distribution function); thus, setting $E_x = 0$ gives the maximum expected revenue. From (3), the optimal seat reservation level x satisfies

$$F(x) = 1 - r. \tag{4}$$

The above is known as the Expected Marginal Seat Revenue (EMSR) model [11, 12].

A similar model allows one to determine the optimal overbooking limit. Suppose that the cost (revenue loss, or *spoilage*) of flying an empty seat due to one passenger not showing up for the flight is 1 (without loss of generality). To avoid this, the airline sells x extra tickets for the flight (in excess of the plane capacity). However, due to this overbooking practice, too many people may show up and some of them will be denied boarding. Let r denote the denied boarding (and recommendation) cost that the airline incurs then for one passenger (the cost may include passenger lodging costs, loss of passenger goodwill, monetary compensations, and so on). Finally, let F be the (cumulative) distribution function for the number of no-shows (as with the seat reservation, airlines can estimate and infer F from modeling and historical data). The revenue loss is $Y - x$ if more than x passengers did not show up ($Y > x$), and is $r(x - Y)$ if $Y < x$. The expected revenue loss (or cost) is thus

$$\begin{aligned} E(x) &= \sum_{y>x}(y-x)\mathrm{P}\{Y=y\} + \sum_{y<x} r(x-y)\mathrm{P}\{Y=y\} = \\ &\sum_{y>x} y\mathrm{P}\{Y=y\} - x(1-F(x)) + rxF(x) - r\sum_{y<x} y\mathrm{P}\{Y=y\} \sim \\ &\int_{y>x} yf(y)\mathrm{d}y - x + xF(x) + rxF(x) - r\int_{y<x} yf(y)\mathrm{d}y, \end{aligned} \tag{5}$$

where we again replace the sum with an integral (assuming F is continuous, as with EMSR). Differentiating this gives

$$\begin{aligned} E_x &= -xf(x) - 1 + F(x) + xf(x) + rF(x) + rxf(x) - rxf(x) = \\ & rF(x) - 1 + F(x) = 0, \end{aligned} \tag{6}$$

when

$$F(x) = \frac{1}{r+1}, \tag{7}$$

which is the desired minimum because the second derivative $E_{xx} = (r+1)f(x) \geq 0$.

III. Basic Tradeoffs: Delays vs. RTTA

We simulated drone traffic over Norrköping municipality in Sweden, using the Cal model [13–15] (which we developed earlier with UC Berkeley – hence the name Cal). Many features of the model are similar to the ones used in [5], e.g., straightline routing and Poisson demand; the spatial scale of our simulations was also similar to the one in the package delivery scenario in [5] (12km), as was the speed of 25m/s of our drones. We simulated the traffic over 12 hours which was sufficient to obtain statistically meaningful results, as the outputs did not vary much from hour to hour. As in [5], we used ground delay for the deconfliction. The main difference of our Cal model from the setup in [5] is that the latter had point sources (origins of the flights) and sinks (destinations) of two types – point and area sinks (the destinations were drawn from Gaussian distribution); our Cal model assumes a slightly more realistic scenario of the traffic demand proportional to the population density – both the origin and destination types are area sinks. Because both the sources and the sinks are spread over the whole city, we used higher traffic intensities (thousands requests/hr) and larger conflict radius (150m) than those in the scenario in [5] (25-250 requests/hr and 50m resp.): with low traffic intensity and small conflict radius (i.e., rare conflicts), RTTA did not have a profound effect on the delays.

To model the uncertainty, we postulate that U-plans may be canceled. Canceling close to the start of the flight is less likely than canceling well before the flight: we modeled the probability of cancellation as a decreasing linear function of the file-ahead time (falling from 10% probability of cancellation at 24 hours before the start – the upper bound on the file-ahead time in our experiments – to 0% at 10 minutes before the start – see Fig. 4). Following the RTTA principles outlined above in Section I, any flights past their RTTAs were frozen: they were flying as scheduled. For example, if flight C-D is delayed because it conflicts with a flight A-B, then even if flight A-B is canceled, the flight C-D will nevertheless start delayed (refer to Fig. 1 for an illustration) – again, the logic is that after RTTA the operator prefers to have no changes (even if now a change would be favorable) because the operator does not have a reasonable time to act on the change (update the delivery time, reschedule charging, etc.).

Figure 5 shows the delays as function of RTTA. With small RTTA there are fewer flights for which the airspace is reserved, and they mostly fly with small delays. With larger RTTA, the airspace is reserved for more flights, and the delays are larger on average. This illustrates the tradeoff between the delays (longer delays are bad) and RTTA (the larger RTTA is, i.e., the earlier you know about your delay the better—even if the delay itself is slightly larger—as this gives you more time to act on the delays, signifying the name Reasonable Time to Act).

To determine a break-even point when some cost related to RTTA is at the minimum, we let RTTA influence the cost (or price, $P(D)$, in terms of [5]) associated with a delay D: we use a simple formula

$$P(D, RTTA) = [D - c \cdot RTTA]_+ \tag{8}$$

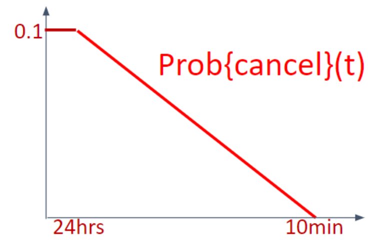

Fig. 4 An input to our model: Probability of canceling the plan as function of file-ahead time before the desired flight start.

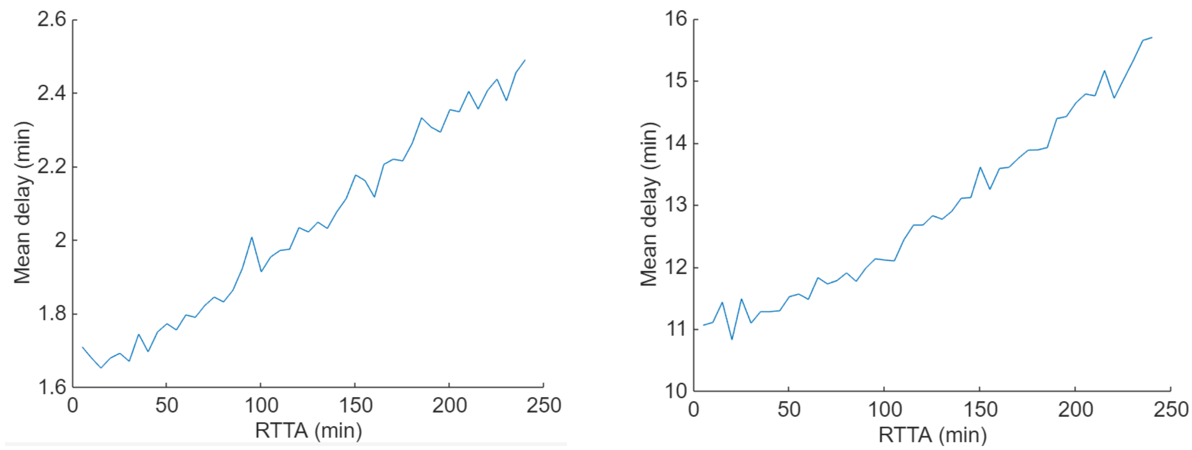

Fig. 5 Average delay per flight. Left: 850 requests/hr. Right: 1700 requests/hr.

for the price of knowing about the delay D at the time $RTTA$ before the departure, where $[x]_+ = \max(0, x)$ (the price should not be negative, i.e., the operator does not get profit from knowing about the delay early). The constant c determines the relative importance of RTTA (having time to act, after learning about the delay) vs. the price of the delay.

Figure 7 shows the price as function of RTTA for various values of the "RTTA importance constant" c. For $c = 0$ the price is just the delay (the top line on the plots in Fig. 7 are the same lines as in Fig. 5, left top and bottom), so the minimum price is at RTTA = 0. As c increases, the importance of RTTA (knowing about the delays earlier) grows, and hence the minimum price is attained at larger and larger RTTA. However, when c is large, $c \cdot RTTA$ becomes larger than the delay, and the price drops to 0 for many flights (recall from the price formula (8) that we do not allow negative prices) – such operations do not benefit from higher RTTA, and hence the optimal RTTA (minimizing the total, or average price) decreases. Overall this implies that there is no need to increase RTTA past certain value (the value itself may depend on the demand: when the traffic intensity is higher, the operators may want to know about their delays earlier than in a low-traffic scenario).

By analogy with the EMSR (2) and overbooking (5) models, we can write the expected price as

$$E(P(RTTA)) = \int P(D, RTTA)\, f(D)\, \mathrm{d}D = \int_0^\infty [D - c \cdot RTTA]_+ f(D)\, \mathrm{d}D =$$
$$\int_{c \cdot RTTA}^\infty (D - c \cdot RTTA)\, f(D)\, \mathrm{d}D = \int_{c \cdot RTTA}^\infty D\, f(D)\, \mathrm{d}D - c \cdot RTTA \int_{c \cdot RTTA}^\infty f(D)\, \mathrm{d}D = \tag{9}$$
$$\int_{c \cdot RTTA}^\infty D\, f(D)\, \mathrm{d}D - c \cdot RTTA(1 - F(c \cdot RTTA)),$$

where f, F are the probability density and the cumulative density functions resp. of the delay D. Similarly to EMSR (3)

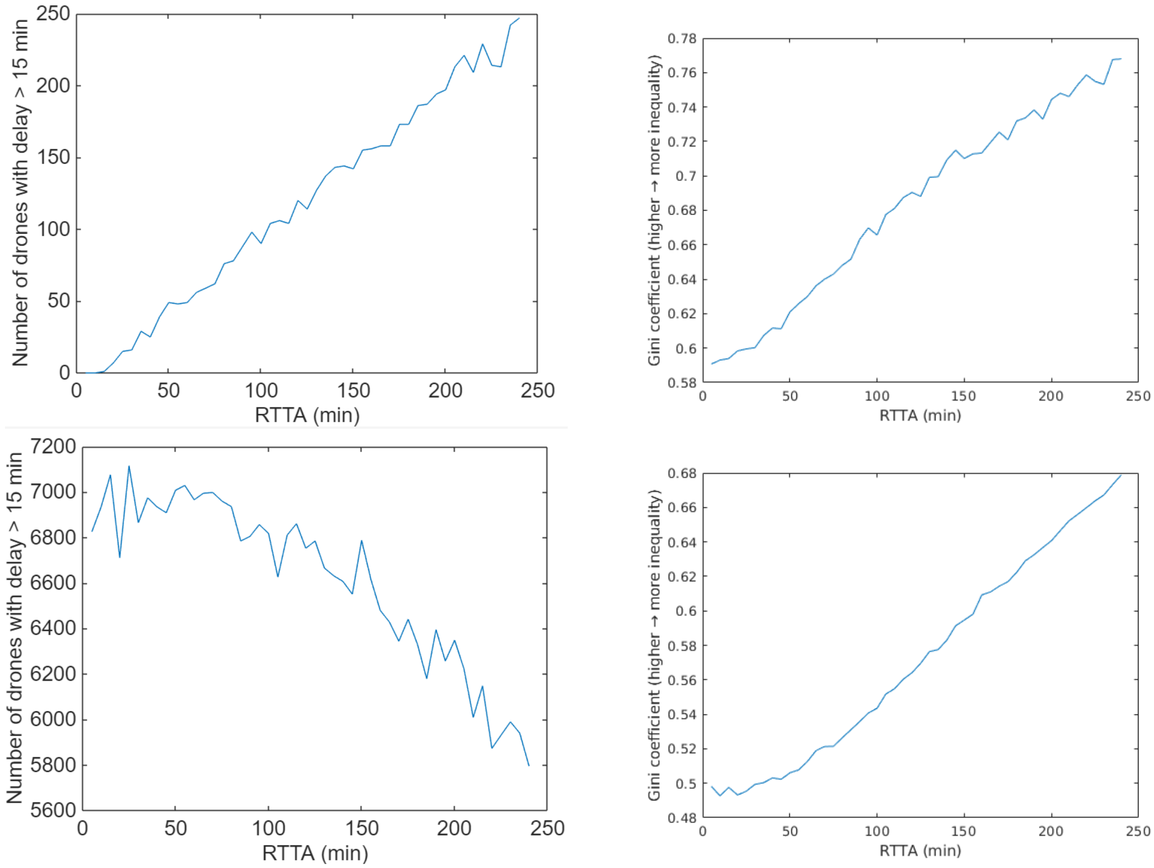

Fig. 6 Number of flights delayed by more than 15 minutes (left) and the Gini inequality coefficient of the delays where 0 represents complete equality and 1 is complete inequality (right). Top row: 850 requests/hr. Bottom row: 1700 requests/hr. Note that the left graphs have the common threshold of 15min for the long delays: for the low demand (top), 15min is much larger than the average delay and the number of long delays grows, contributing to the increasing average; for the high demand (bottom), the airspace is almost at its capacity, so the already overly delayed flights that experience many conflicts along the way (e.g., due to flying through the congested areas) become even more delayed, thus counter-intuitively freeing the airspace for other, less delayed, operations. The right graph shows how the Gini coefficient of delays grows, representing how the unfortunate over-delayed flights move further and further away from the mean.

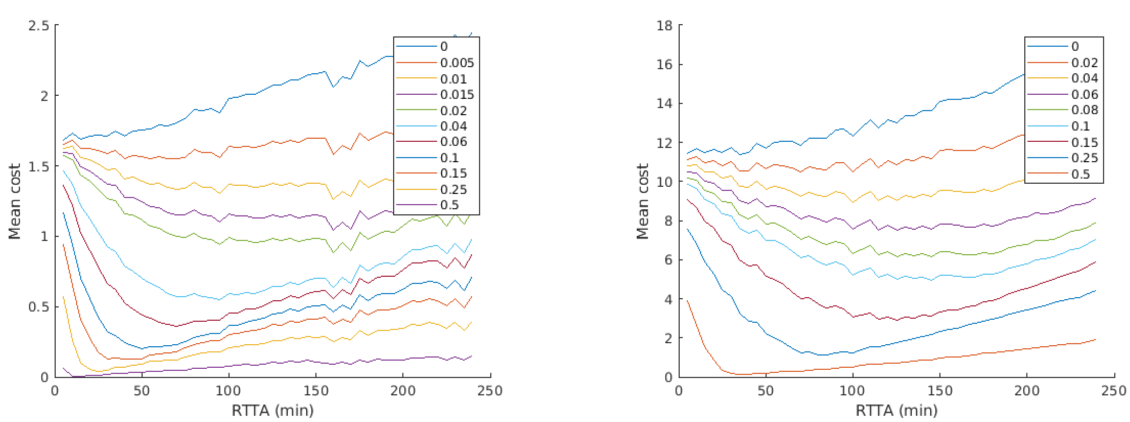

Fig. 7 The price as a function of RTTA for various c (one graph per value of c). Left: 850 requests/hr. Right: 1700 requests/hr.

and overbooking (6), to find the minimum of the expected price, we set the derivative of (9) to 0:

$$\frac{\mathrm{d}}{\mathrm{d}\,RTTA}\int_{c\cdot RTTA}^{\infty} D\,f(D)\,\mathrm{d}D \quad - \quad c(1-F(c\cdot RTTA)) \quad + \quad c^2\cdot RTTA\cdot f(c\cdot RTTA) \quad =$$

$$\begin{aligned} = \quad & \int_{c\cdot RTTA}^{\infty} D\,\frac{\mathrm{d}\,f(D,RTTA)}{\mathrm{d}\,RTTA}\,\mathrm{d}D \quad - \quad c^2\cdot RTTA\cdot f(c\cdot RTTA) \quad - \\ & - \quad c(1-F(c\cdot RTTA)) \quad + \quad c^2\cdot RTTA\cdot f(c\cdot RTTA) \\ & = \quad 0. \end{aligned} \tag{10}$$

That is, the optimal RTTA satisfies

$$\int_{c\cdot RTTA}^{\infty} D\,\frac{\mathrm{d}\,f(D,RTTA)}{\mathrm{d}\,RTTA}\,\mathrm{d}D \quad = \quad c^2\cdot RTTA\cdot f(c\cdot RTTA). \tag{11}$$

Unlike with EMSR and overbooking, the first term in (10) (the left-hand side in (11)) cannot be written out in closed form (because the delay is a function of RTTA); therefore we used the above-described simulations to determine the minimum.

To further highlight the analogy between EMSR/overbooking and RTTA, we first put EMSR and overbooking into a single framework, by identifying our losses (or prices we pay) from our wrong decisions (the framework unifies the formulas (4) and (7)):

For business seat reservation, the prices are

- if x is too high (too much reserved), we loose r per seat – the price increases with x
- if x is too low (no advance reservation), we loose $(1-r)$ – the price decreases with x

For overbooking, the prices are

- if x is too high (plane overbooked), we loose r per passenger – the price increases with x
- if x is too low (ignored no-show), we loose e per pax – the price decreases with x

For RTTA the prices of our wrong decisions are

- If RTTA is too high (airspace overbooked), the extra price is $[D-c\cdot RTTA]_+ - D(0)$ – increases with RTTA
- if RTTA is too low (no advance reservation), the price is $[D-c\cdot RTTA]_+$ –decreases with RTTA

We again note that, unlike with the EMSR and overbooking, D is a function of RTTA (the "decision variable"), which precludes deriving closed-form formulas for the optimum à la (4) and (7) (i.e., simulations are needed).

IV. Quantifying Influence of Weather Uncertainty

Weather—one of the main sources of uncertainty in ATM—is a major player also for drone traffic. For larger lookahead time, the uncertainty of the weather forecast increases, i.e., the forecast becomes more and more precise as it approaches nowcast. One crucial parameter influenced by the lookahead time of the forecast is the minimum separation distance between drones: the longer the lookahead time, the greater the uncertainty, which requires drones to be spaced farther apart to avoid collisions or interference caused by unpredictable weather conditions. Thus, if the drones are deconflicted earlier (longer time before the flight, i.e., with larger RTTA), the radius r of the protected airspace around each drone increases, which leads to the decrease of the airspace capacity (fewer flights can be routed so that the radius-r disks, centered on the drones, do not overlap while the drones fly). This way additional delays are incurred, if the weather uncertainty is taken into account.

We quantify the weather infuence by applying the RTTA analysis techniques developed in the previous section. We ran the same simulations as in Section III, but with the radius r dependent on the RTTA: we use a simple dependence of $r = r_0 + c_w \times$RTTA where r is in meters, RTTA is in minutes (if a flight request was submitted past its RTTA, we use the time request submission and intended departure instead) and $r_0 = 150$m is the radius used in Section III assuming perfect weather forecast (our techniques extend to any other model of how the forecast uncertainty grows with the lookahead time). We fix the value of the "RTTA importance constant" $c = 0.1$ and look at different values of c_w which represents how the safety radius around drones increases with the lookahead time. Figure 8 shows the price as a function of RTTA with the weather uncertainty taken into account. It can be seen that for larger c_w (i.e, with the larger weather influence), the optimal RTTA is smaller (i.e., the U-plans should be deconflicted closer to their departures) – our results quantify this intuition.

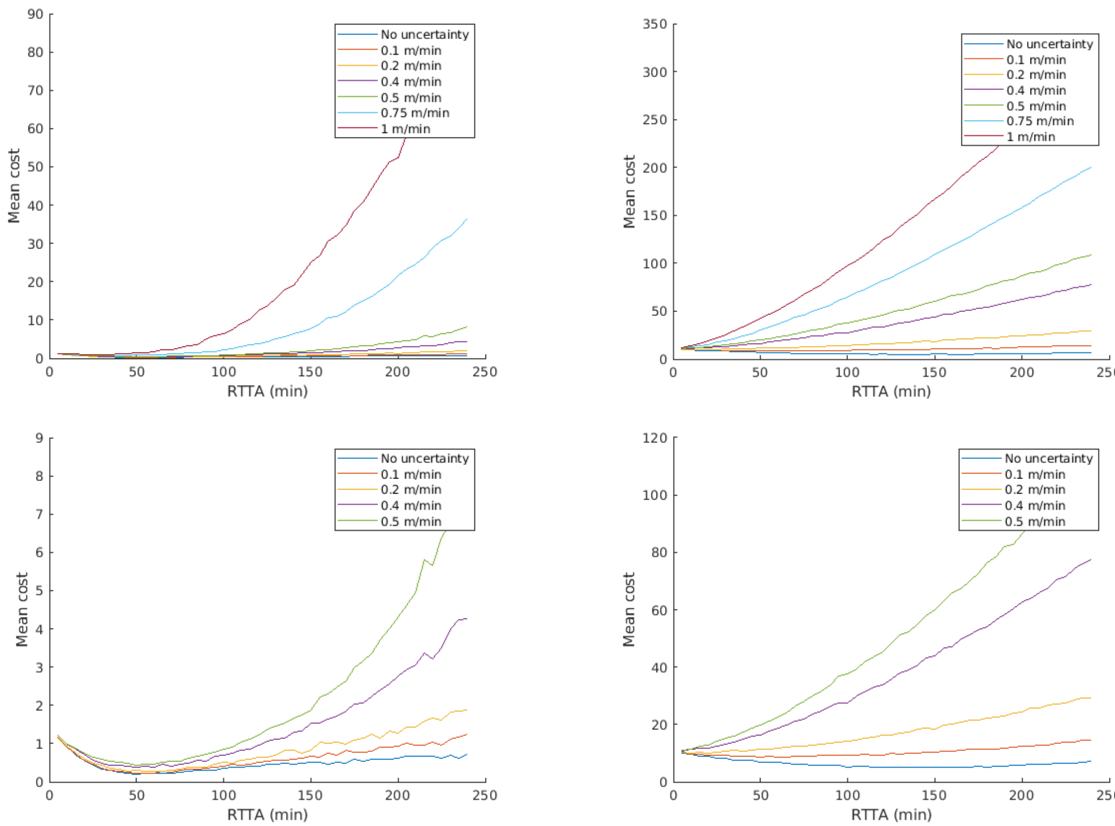

Fig. 8 The price as a function of RTTA for various coefficients of weather uncertainty c_w (one graph per value of c_w). Left: 850 requests/hr. Right: 1700 requests/hr. The bottom row is the same as the top row but zoomed in on the lower values of c_w.

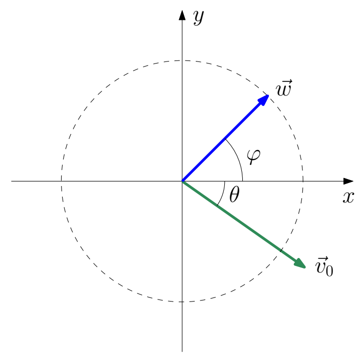

Fig. 9 The y component of the wind is canceled, so the drone moves in the positive x direction.

A. Wind uncertainty

For drone traffic, one of the most influential weather phenomena is wind. In this subsection, we explore how wind prediction uncertainty may affect the delays at different RTTAs. We do not perform any fine-tuned kinematic modeling of the trajectories; instead, we only consider the average effect winds have on the strategic deconfliction.

Assume that the speed $v_0 = 25$m/s used in our simulations above is the maximum drone speed and that the drone stays on course even in windy conditions (we assume that the wind is the same in the whole region of interest): under the wind $\vec{w} = (w\cos\varphi, w\sin\varphi)$ (where $w = |w|$ is the wind speed and φ is its angle with the x-axis), the drone whose course is the x-axis, propels in the direction θ such that $|v_0 \sin\theta| = |w \sin\varphi|$ (Fig. 9), so the drone's speed becomes

$$s \quad = \quad w\cos\varphi + v_0\cos\theta \quad = \quad w\cos\varphi \; + \; v_0\sqrt{1 - \frac{w^2}{v_0^2}\sin^2\varphi}.$$

We use a simple probabilistic model in which the wind direction is uniformly distributed in $[0, 2\pi]$ (w thus measures the wind uncertainty) and the drones speed is expected to be

$$v \quad = \quad \frac{1}{2\pi}\int_0^{2\pi} s\,\mathrm{d}\varphi \quad = \quad v_0\,E\left(2\pi, \frac{w}{v_0}\right),$$

where E is the elliptic integral of the second kind – we postulate that all flights should be planned with that reduced speed in order to account for the uncertainty (our techniques extend to any other uncertainty model and to accounting individual effect of wind on every drone; such extension, to more realistic weather models with prevalent winds directions etc., is left for future work).

We ran the same simulations for the RTTA analysis as in Section III to explore how wind speed uncertainty influences the costs. To keep the results as general as possible, our experiments did not assume any specific dependence of the uncertainty on lookehead time (the uncertainty is determined by the weather prediction service and may be supplied along with the prediction), and instead look at different fixed values of the wind speed uncertainty $w \in \{0$ m/s, 5 m/s, 10 m/s, 15 m/s, 20 m/s$\}$. We set the value of the "RTTA importance constant" $c = 0.1$ and a use the safety zone radius $r_0 = 150$ m. Figure 10 shows how the cost changes with RTTA under different values of w.

V. Conclusion

We explored how RTTA (the time before the flight when the U-plans are deconflicted) influences the delays. We also quantified the weather uncertainty influence. Future work may consider other costs/profits associated with the delays and RTTA. Also, other dependencies of the separation standard r on RTTA may be used; in this paper we only outlined the methodology to quantify the weather impact on RTTA. Last but not least, more extensive simulations may be run to produce the distributions of various KPIs for different values of RTTA. These KPIs could inform how RTTA settings are regulated, translating to the kinds of common references such as the COPs mentioned previously in Section II.

Acknowledgments

This research is partially supported by the Swedish Transport Administration, the Swedish Research Council and Catalyst funding – a project supported by the SESAR 3 Joint Undertaking and its founding members under the Grant

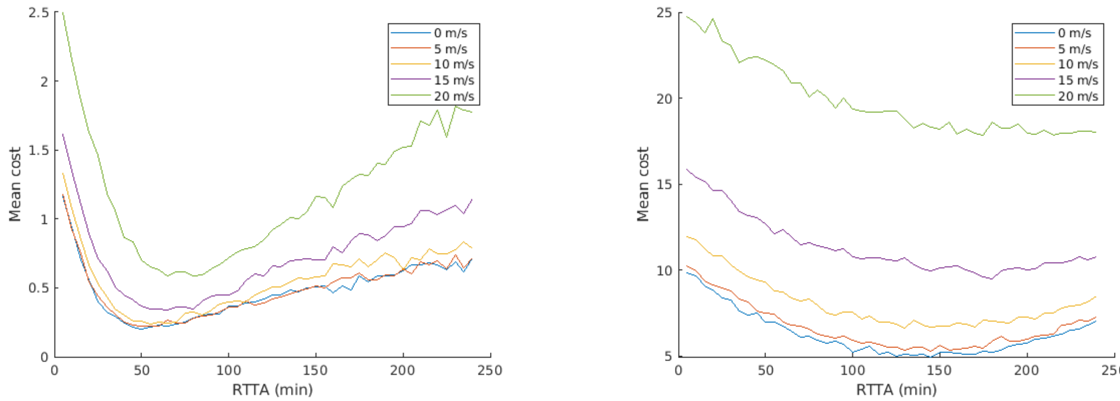

Fig. 10 The price as a function of RTTA for various coefficients of wind uncertainty w (one graph per value of w). Left: 850 requests/hr. Right: 1700 requests/hr.

Agreement nr. 101114648. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or SESAR 3 JU. Neither the European Union nor the SESAR 3 JU can be held responsible for them.

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