

Safe, Efficient, and Fair UTM Airspace Management

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Abstract—Unmanned Aircraft Systems (UAS) are increasingly used to perform crucial commercial activities such as various types of inspections (crops, railroads, and bridges), surveillance, and package delivery. Regulators have become interested in developing UAS Traffic Management (UTM) systems. One promising framework for UTM allocates airspace to UAS operators via an auction. To succeed, an airspace auction must be economically efficient, fair, scalable, incentive-aligned, simple, and capable of continuously modeling airspace and sharing bid status and pricing information. This paper introduces the first airspace auction mechanism that meets these criteria. In the process, we introduce new spatial-temporal fairness constraints and a new abstraction for communicating airspace pricing information, the airspace price field. We evaluate our mechanism on UAS delivery scenarios taken from a Japan Aerospace Exploration Agency (JAXA) study and show that it scales to 1000s of bids.

I. INTRODUCTION

Over the last decade, various industries have rapidly adopted unmanned aircraft systems (UAS). UAS are known for their low cost flight operations, maneuverability, and vertical take-off and landing (VTOL) capability [1]. This makes them suitable for remote sensing (surveillance and inspections) and package delivery. The number of UAS registered with the FAA for commercial usage increased from 12,000 in 2016 to 328,000 in 2022. This explosion in UAS flight operations has led to the research and development of UAS Traffic Management (UTM) to coordinate UAS missions in the National Airspace Systems (NAS) [1, 2, 3, 4, 5].

II. BACKGROUND AND MOTIVATION

A. UTM Airspace and Conflict Management

This work fits inside a broad research effort to develop and evaluate technologies designed to address operational challenges of deploying small UAS (≤ 55 lbs) in dense and low altitude (≤ 400 ft AGL) urban environments [6] [7] to deliver goods. These efforts will result in a set of services in a decentralized, “federated” framework, defined as “a set of services [which] enables cooperative management of operations between UAS Operators, facilitated by third-party support providers through networked information exchanges” [1]. The federated approach would ensure on-demand mobility in the transportation of passengers and cargo in a safe and efficient manner that ensures public acceptance [8].

The FAA and NASA envision UTM having a multi-layer conflict management model to ensure the safe, efficient, and

scalable operations of UAS. These layers are referred to as strategic deconfliction, tactical deconfliction, and collision avoidance [2, 3]. At each layer, conflicts are resolved through a series of maneuvers compatible with the operational environment. The objective of the first layer of the conflict management model, i.e., strategic deconfliction, is to minimize the likelihood of airborne conflicts between UAS operations and maximize the airspace usage by adjusting the departure times of UAS [1, 3]. Choosing which flight path to allocate to a UAS is a hard problem. During pre-departure, simple flight path selection schemes such as the best equipped first-come-first-served often allocate airspace inefficiently and unfairly. It is commonly accepted that for strategic and tactical deconflictions kinds of deconfliction are needed for UTM to ensure safety, efficiency and fairness [9] [10].

B. Auction-based Allocation and Deconfliction

Combinatorial auctions have a long history as a mechanism for allocating public goods such as spectrum [11], as well as transportation and delivery services such as exchanging transportation requests between freight carriers [12], matching carriers and shippers [13, 14], airport time-slot allocation [15] and delivery logistics [16]. Recently, combinatorial auctions have been proposed as a framework for UTM [17]. Our auction mechanism is the first, however, to achieve the broad range of criteria necessary for UTM operations. The challenge of solving the winner determination problem for a combinatorial auction at scale is well-studied. Proposed approaches use depth-first and breath-first search [18, 19], branch-and-bound [20], and decision-trees [21].

C. Multi-agent Path Finding

The problem of Multi-Agent Path Finding (MAPF) solving for deconfliction is well studied, including highly scalable search-based MAPF solvers [22, 23] and rule-based [24] methods. Traditional MAPF solvers, however, do not contain mechanisms to incentives bidders to honestly report their valuation flight path valuations. Recently, MAPF solvers have been proposed that incorporate private incentives [25, 26, 27, 28]; as well as privacy protection [29]. No MAPF solver, however, currently provides economic-efficiency, fairness, truthfulness and scalability simultaneously. More recently, path finding for autonomous agents using Multi-agent Reinforcement Learning

(MARL) [30] has been proposed to train agents that are robust to changes in the environment.

D. Motivation

This research aims to develop a safe, efficient, and fair airspace allocation scheme for selecting non-conflicting airspace volumes (flight paths). This paper presents a model for pre-departure strategic deconfliction and allocation of airspace using a token-based airspace-auction. This approach has four key novel features:

- 1) A quantification of bidder utility using a token distribution system.
- 2) An auction-based strategic deconfliction mechanism.
- 3) A novel visual display for communicating preferences among UAS operators using the concept of a price field.
- 4) An empirical evaluation of the system with realistic scenarios based on a JAXA UTM study.

Overall, we seek to show that an auction-based framework is feasible for performing strategic deconfliction in UTM.

The remainder of this paper is organized as follows. In section III, we define the problem of strategic airspace allocation and deconfliction and the technical approach based on combinatorial auctions. In section IV, we summarize the implementation and the tests conducted thus far on realistic scenarios. Finally, Section V presents conclusions and plans for future work.

III. PROBLEM FORMULATION

In this section, we formalize the airspace allocation problem (AAP). Informally, an AAP takes as input a set of *flight paths* defined over an airspace, where each path is a sequence of volumes in the airspace. Each path is associated with a number indicating its value or utility. The problem is to generate a subset of Π which are pairwise de-conflicted, and which maximises the sum of the values of the individual paths.

In more detail, the AAP consists of:

Airspace. Airspace C is a 4D space with 3 spatial dimensions and 1 time dimension. Infinitesimal airspace elements are denoted $dr \in C$.

Flight Paths A flight path $\pi \subseteq C$ is a subset of airspace.

A flight path is represented with a set of convex 3D polyhedra (volumes). Each polyhedron has a start and end time, representing the times by which a UAS may enter and must leave the polyhedron, respectively. We combine a path with a number v indicating its value, and let $V(\pi)$ be a function returning this value. We call the pair (π, v) a *request* for airspace. We let Π denote a set of requests.

Conflicts A pair of flight paths π, π' are conflicted if one or more of their volumes overlap. A set of flight paths is deconflicted if no pairs of paths are in conflict.

The Airspace Allocation Problem (AAP) Given a tuple (C, Π) of airspace and set of requests, generate a set $\Pi_d \subseteq \Pi$ which is deconflicted and whose sum of the values of the paths in Π_d is maximized. That is,

$$\Pi_d = \max_{P \subseteq \Pi} \sum v(\pi)_{\pi \in P}$$

This formulation of the AAP can be solved using standard approaches from Graph theory; in particular, the AAP maps directly to the Maximum Weighted Independent Set (MWIS) problem. We utilize this approach in our overall solution, which is discussed below. Solving the AAP in isolation using an MWIS solver is a way to ensure safety through deconfliction and also achieves a form of economic efficiency through maximizing the values of the set of deconflicted paths. However, this solution is incomplete without a deeper exploration of the federated UTM environment in which this solution is to be deployed, in which airspace allocation and deconfliction is a collaborative process between UAS operators and the UAS Service Supplier [1]. Therefore, it is important to add to this framework an infrastructure for *collaborative* airspace allocation.

Broadly speaking, an infrastructure for collaboration will minimally include mechanisms for the communication of preferences among UAS operators, as well as for achieving a high standard of fairness among the players. In the next section, we propose that a combinatorial auction mechanism provides a robust, expressive infrastructure for solving the AAP in a federated environment.

IV. TECHNICAL APPROACH

The proposed federated approach to airspace allocation is a hierarchical economic organization in the form of an administrative procedure [31]. Unlike its market-based cousin, an administrative procedure has a centralized component which deconflicts and allocates airspace. Unlike traditional committee-based administrations such as that used for airport operations or gas pipeline allocation, we propose a *combinatorial auction mechanism* to administer airspace.

A. Auction Mechanism Using a Token Framework

We re-formulate the AAP as a combinatorial auction, where a set of bidders bid on a bundle of volumes of airspace. Initially, we assume that there are no restrictions on the airspace being auctioned; later we discuss ways in which to impose restrictions to guarantee fairness. Second, we describe an iterative auction scheme consisting of a set of rounds.

1) *Bid Expression and Token Scheme:* A set of bidders $\beta_1 \dots \beta_n$ correspond to UAV operators participating in an airspace auction. Each bidder β_i is associated with a set of missions $M_i := \{m_{i1}, m_{i2} \dots\}$, minimally consisting of a start and goal location. For each mission m_{ij} , a bidder needs to obtain a flight path, a set of space-time cells $C' \subseteq C$ that a UAS can fly through. A bid $b_i := (\beta_i, C_i, v_i)$ is a (bidder, flight plan, value) tuple, indicating that bidder β_i will pay up to value v_i for flight plan C_i .

Assuming the set C of airspace volumes is large, it is important to reduce the burden of specifying all the combinations of items to bid on. One simple way to make the bidding language more expressive is to allow *XOR constraints* to arrange bids. An XOR bid $x_j := \{b_1, b_2, \dots\}$ is a set of bids, with the condition that at most one of the bids $b_1, b_2, \dots$ should win.

An XOR bid improves the ability for bidders to specify a set of alternatives to fly for a single mission.

The winner determination problem for a combinatorial airspace auction maps directly to the AAP defined in the previous section, where requests are represented as bids, and the additional constraint is added whereby the winning set Π_d does not contain a pair of bids from the same XOR bid.

To express values associated with bids, we impose a *token framework*, whereby the value of a bid is expressed as the number of tokens the bidder is willing to spend. Tokens, like play money or chips in a poker game, have no intrinsic monetary value, but are accepted as a proxy for the monetary value the bidder is willing to spend to gain the requested airspace. Unlike games, the goal is not for any operator (or indeed the auctioneer!) to 'win' by acquiring the most tokens. At its core, a token framework is simply a way to quantify and communicate operator preferences, where the latter map to maximizing the number of missions flown. Imposing a token framework in the context of airspace auctions has complexities which we discuss further below.

2) *Iterative Auctions and Preference Elicitation*: An iterative combinatorial auction addresses the difficulties that arise in determining the valuations of bids and communicating them [18]. An iterative CA allows bidders to submit multiple bids and receive information feedback that allows the bidders to revise their bids, thus providing recommendations to support bidders.

Figure 1 shows the components of an iterative airspace auction. On the left (green) a UAV operator is iteratively submitting bids and querying useful information about the state of the auction. In the middle are the ways the bidders interact with the auction framework. On the right are the processing units of the auction framework (in blue) and the inputs and outputs of the system (grey).

As shown in the figure, bidders can interact with an auction in one of three ways:

- 1) Submit a New Bid or update the price of a previous bid. At the onset of an auction, a bidder submits a set of XOR bids, one for each mission to be flown. Later in the auction, as more information is acquired, the bidder may update any of its bids, either by adding to deleting bids from an XOR bid, or increasing the price of an existing bid.
- 2) Query the Current Price of a Flight Path. The current price of a flight path is the minimum price that a new bid on this flight path must have to win, assuming no further bids are submitted. Sharing information about the current price of a flight path allows bidders to identify well-priced flight paths to bid on.
- 3) Request a Price Heatmap for a Region of Airspace. To communicate the state of the auction efficiency, we allow bidders to request a heatmap of the prices of each cell in a region, where the price of a cell is the price of a flight path which only contains that cell. Knowing the price of a cell allows a bidder to quickly know the lower-bound the cost of any flight path which contains that cell.

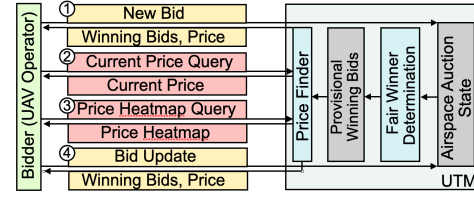


Fig. 1. The Components of an Iterative Airspace Auction

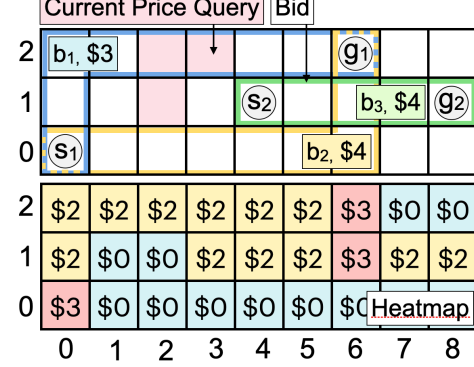


Fig. 2. A Heatmap.

Among of things, lower-bounding the price of a flight path allows a bidder to rule it out if it is out-of-budget.

B. Requesting a Price Heatmap for a Region of Airspace

Example Price Heatmap. Figure 2 (bottom) shows a price heatmap for the example airspace auction. This price heatmap associates the cell (0,0) with the price \$3, indicating that any flight path that contains cell (0,0) has a current price of at least \$3. It can be shown that the current price of a flight plan $C' \subseteq C$ is at least the current price of any cell $c \in C'$ in that flight path. This information provides necessary and useful information to an operator to ensure a future bid is competitive.

C. Winner Determination and Pricing

In the iterative auction, an initial set of bids is submitted and evaluated, followed by an update of the auction state, which is displayed in the heat map. Eventually, the auction is closed and a fair winner determination function selects the set of winning bids (Figure 1, 6-7).

The set of winning bids is a solution to the AAP, i.e., a deconflicted set of bids with maximal value, with at least one bid selected from each XOR bid. Formally, a set of bids $\omega \subseteq B$ is a valid solution to the AAP if:

Property 1. Any bid $b_i \in \omega$ only contains cells that are up for auction.

$$\forall (\beta_i, C_i, v_i) \in \omega, C_i \in C'.$$

Property 2. No two bids $b_i, b_j \in \omega$ share a cell or an XOR constraint.

$$\forall b_i, b_j \in \omega, C_i \cap C_j = \emptyset \wedge \neg \exists x_k \in X \text{ s.t. } \{b_i, b_j\} \subseteq x_k.$$

Given an auction state (C', B, X) , let $\Omega(C', B, X) \subseteq 2^B$ be the set of all sets of valid bids. Let the value $v(\omega)$ of a set of bids ω be the sum of those bids' values:

$$v(\omega) := \sum_{b_i \in \omega} v_i.$$

The winner determination function $air(C', B, X)$ selects a maximal value, valid set of bids.

$$air(C', B, X) \in \operatorname{argmax}_{\omega \in \Omega(C', B, X)} v(\omega)$$

Pricing. Once a provisional set of winning bids has been determined, the system determines the provisional price that every bidder has to pay for winning bids. We propose the standard Vickery-Clarke-Groves (VCG) pricing scheme, where a bidder is charged for the decrease in value that their presence causes other bidders. In other words, a bidder β_i is charged:

- the value of the set of bids that would have won if bidder β_i had not bid
- minus the value of the set of bids submitted by other bidders $\beta_j \neq \beta_i$ that did win.

A VCG pricing scheme has the advantage of making it optimal for a bidder's bids to reflect their true valuation of a flight path. We now formalize our pricing scheme. Let bidder β_i 's

- set of bids and XOR constraints be B_i and X_i
- set of winning bids be $air_i(C, B, X) \subseteq air(C, B, X)$
- valuation of her winning bids be $airv_i(C, B, X) := v(air_i(C, B, X))$.

Let $airv(C, B, X)$ be the total value of the winning bids:

$$airv(C, B, X) := v(air(C, B, X)) = \sum_i airv_i(C, B, X).$$

The price p_i that bidder β_i is charged is:

$$p_i := airv(C, B/B_i, X/X_i) - \sum_{j \neq i} airv_j(C, B, X).$$

At the close of the auction, each bidder is sent her current set of winning bids and the current price that they are being charged for them. Alternatively, if the airspace auction is still open, a bidder can respond by placing new bids and increasing the price of previous bids.

D. Achieving Fairness

Fairness has been defined as inequity aversion: an agent is willing to give up some material payoff to move in the direction of more equitable outcomes for everyone [32]. An equitable outcome in airspace allocation roughly means an allocation that produces the greatest value for the most operators.

An agent will advocate fairness for many reasons, including:

- *Self-centered inequity aversion* [32]. The agent does not want to be a victim of unfairness by others.
- *Social Responsibility*. The agent realizes that certain needs of others are more urgent/important (e.g emergency services require priority in allocating airspace);
- *Altruism*. The agent is willing to give up a little material value for the common good (e.g., choosing a slightly

less optimal chunk of airspace helps others achieve their goals); or

- *Ceteris paribus rules*. For example, the agent believes that ordering allocations based on *first-come first-served* is fair.

A competitive, mostly non-cooperative environment such as commercial UAS operations presents challenges in ensuring fairness. In general, we assume here that the set of operators participating in the airspace auction commit to varying degrees of inequity aversion. For example, we may assume that all players are averse to unfair behavior in others, have some degree of social responsibility, and accept some ceteris paribus rules such as first-come-first-served. At the same time, some operators may at times resort to unfair behavior in order to benefit themselves.

To achieve a fair allocation, there are a set of changes to the winner determination algorithm that need to be made. In particular:

- 1) To identify potentially unfair practices, the system can impose further constraints on the bids submitted or on the solutions obtained (an example appears in the next section);
- 2) To enforce socially responsible outcomes, it may be possible to create a multi-tiered approach to allocation. For example, medical or other high priority paths are allocated first, followed by package delivery requests.
- 3) Ceteris paribus rules like first-come first-served may be enforced through an ordering of the processing of bids.

Altruistic behavior, on the other hand, might be difficult to achieve using a centralized authority such as the UAS. It suggests a peer-to-peer approach between different agents, who can directly negotiate trades to achieve mutual benefit. These issues are beyond the scope of this paper.

These paragraphs on fairness have been a preliminary attempt to identify how a centralized service such as UAS can include fairness into the airspace allocation and deconfliction process. This is a relatively unexplored area of focus, and more work is needed.

V. IMPLEMENTATION AND EVALUATION

Implementing the airspace auction requires an efficient implementation of the winner determination function $air(C, B, X)$. When a new bid is submitted or the price of a bid is updated, we must compute a new set of winning bids and a new price to charge every bidder. If there are n bidders, we can accomplish this with $n + 1$ executions of the winner determination function. Responding to a bidder querying the price of a flight path C' requires another execution of the winner determination function. Responding to a request for a price heatmap for the set of cells D requires an execution of the winner determination function for each cell $c \in D$.

Winner Determination Function Implementation. The winner determination function $air(C', B, X)$ is implemented with the following ILP formulation. Let a_{ij} denote that cell $c_i \in C$ is allocated to bid b_j and w_j denote that b_j is a winning bid. The value of the set of winning bids is maximized:

$$\max \sum_{b_j \in B} w_j p_j.$$

subject to the following constraints:

Constraint 1. A cell in C' is allocated to at most one bid. A cell not in C' is left unallocated:

$$\forall c_i \in C, \sum_{b_j \in B} a_{ij} \leq \begin{cases} 1 & c_i \in C' \\ 0 & c_i \notin C' \end{cases}$$

Constraint 2. A bid wins iff it is allocated every cell in its flight path:

$$\forall b_j \in B, \frac{\sum_{c_i \in C_j} a_{ij}}{|C_j|} \geq w_j$$

Constraint 3. At most one bid in each XOR constraint can win:

$$\forall x_k \in X, \sum_{b_j \in x_k} w_j \leq 1$$

Constraint 4. The set of bids ω must satisfy all fairness constraints. Fairness constraints are encoded directly into the ILP. For example, the anti-monopoly fairness constraint described previously would be expressed:

$$\forall \text{ bidders } \beta_i, \sum_{b_j \in \omega_i} |C_j| \leq 0.05|C|.$$

Code Base Design. Our auction mechanism was written as a Python 3.11 tool chain. Instances of the winner determination problem are formulated and solved using the Gurobipy library, a Python wrapper for the Gurobi ILP solver.

VI. EVALUATION

The airspace auction framework was implemented and evaluated on eight UAV delivery scenarios based on a JAXA study [33]. The goal of this evaluation on a realistic experimental design was to evaluate the operational feasibility of our auction mechanisms on realistic UAV delivery scenarios at differing density levels.

A. Benchmark Hardware

Each evaluation was performed on a 16 core, 3.2 MHz AMD Ryzen 7 5800h CPU with a 256 KiB L1 Cache, a 4 MiB L2 Cache, a 16 MiB L3 Cache, 13.5 GiB of RAM and 512 GB of disk memory running a 64-bit version of Ubuntu 20.04.6 LTS.

B. Methodology

Our evaluation takes place on scenarios in a 10km by 5km region of the city of Sendai, Japan. The region contains 6 small no-fly-zones which protect public buildings such as Sendai Station. Our scenarios are based on two delivery hub layout models presented in the JAXA study, Model 1 and Model 2, in order to demonstrate how locations of delivery hubs have a significant impact on delivery efficiency by ground vehicles. Model 1 uses existing ground vehicle delivery hubs as drone

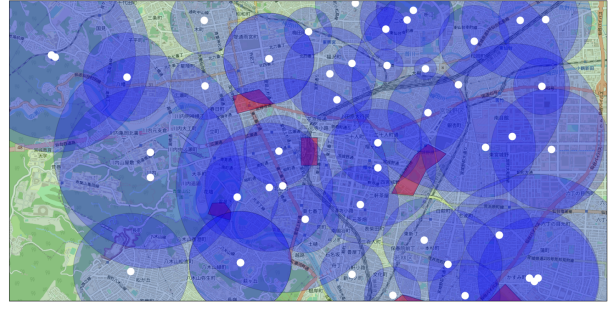


Fig. 3. A map of Sendai, Japan where drone hubs are colored white, hub delivery areas are colored blue, and no-fly-zones are colored red.

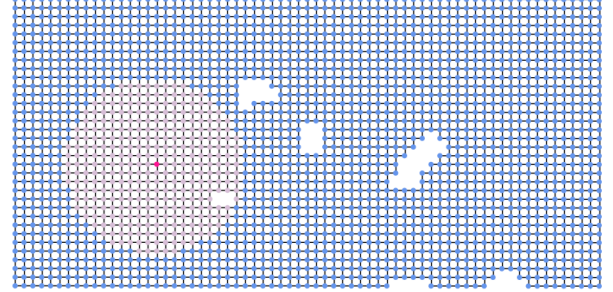


Fig. 4. The set of 150m by 150m by 150m by 3 minutes space-time cells which share a time interval. A single hub vertex is colored red. Vertices in the hub's service area are colored grey.

hubs, whereas in Model 2 public elementary and junior high schools are used as drone hubs. In the model, each hub is associated with one of three operators, a daily mission quota, and a delivery area. Figure 3 depicts each hub in Model 2 with a white cross and the hub's delivery area with a blue circle. No-fly-zones are depicted as red polygons.

By Japanese law, a drone may not fly more than 150m above the ground. The JAXA study suggests drone separation distances of 60m and 150m. We divide time into 3 minute intervals. We therefore consider scenarios with $150m \times 150m \times 150m \times 3$ minute and $60m \times 60m \times 150m \times 3$ minute space-time cells. A grid of $150m \times 150m \times 150m \times 3$ minute space-time cells which share a time interval is shown in Figure 4. Gaps in the grid are depicted in black and correspond to Sendai's no-fly-zones. Hubs are positioned at the nearest cell to their true location and serve cells in their delivery area. Figure 4 depicts the cell that one hub is positioned at in red and that hub's service area in grey.

The JAXA study associates each hub with a daily number of missions. We conduct auctions for 1, 2, and 4 hour periods and scale the number of missions flown out of each hub accordingly. Each mission flown out of a hub delivers a package to a randomly chosen cell in that hub's delivery area. The start time of a mission is chosen at random. We generate 1-4 flight paths for each mission. Each flight path follows a shortest path connecting the mission's hub and delivery location. Flight path construction assumes that UAVs fly at 15 m/s, the flight speed of the Multirotor DJI Matrice600.

A bid is placed on each flight path valued at 100 Yen less the length of the flight path, that is, $100 - |C'|$ Yen. The bids associated with each mission are added to that mission's XOR constraint.

Table 1 shows the model, cell size, auction period of each of the 8 scenarios. Five instances of each scenario were generated and our formulation of the winner determination function run on each. Table 1 shows the number of XOR constraints, bids and cells contained by bids in each of these scenarios. Each auction was run with the example anti-monopoly fairness constraint, encoded into the winner determination function as in the example above.

C. Results

Table 1 shows each winner determination function's mean run time and run time range on each scenario. Each scenario's run times clustered within 10% of each other, suggesting high replicability. Model 1 had longer run times than Model 2 because it had fewer and more densely packed hubs, resulting in more conflicts for the ILP solver to resolve. Winner determination took less than 45 seconds on every scenario, which should be reasonable in an operational setting where flight paths are reserved on an hourly basis. More experiments will be conducted to further justify this claim.

VII. SUMMARY AND FUTURE WORK

The goal of this paper is to introduce a safe, efficient, and fair airspace allocation scheme for selecting non-conflicting airspace volumes for UTM, based on a token-based iterative airspace-auction model for airspace allocation and deconfliction. A complete federated UTM is a distributed semi-cooperative decision-making process involving operators and ISS services, where an "operator ... plans flight/operations, shares operation intent information, and safely conducts operations using all available information." [34]. Extensions to this work being pursued include:

Terminal Delay Management Part of our current effort is to explore operator decision support in the form of scheduling terminal delays as a method of strategic deconfliction, expanding previous work[35].

Fairness One guiding principle for UTM is "The UTM ecosystem ensures that availability and access to airspace takes into account the needs of all stakeholders." [9]. This paper has categorized different kinds of fairness, and in future work we explore ways to implement and test these requirements within the framework proposed here.

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TABLE I
THE TIME REQUIRED BY FL-AIRSPACE TO SOLVE THE WINNER DETERMINATION PROBLEM.

Model	Period (hr)	XOR Cn.	Bids	Cells in Bids	Runtime (sec)
1	1	2239	7873	29046	44.32 -1.70 +2.2
1	2	4478	15603	58596	17.89 -0.54 +0.80
1	1	2239	8501	79486	32.69 -1.17 +0.89
2	1	2110	6619	22854	4.05 -0.10 +0.16
2	2	4220	13228	46696	11.9 -0.10 +0.10
2	4	8440	26421	93126	39.27 -0.62 +1.33
2	1	2110	7743	55426	13.17 -0.12 +0.13
2	2	4220	13228	46696	44.5 -2.79 +1.88

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