Combinatorial Auction-Based Strategic Deconfliction of Federated UTM Airspace

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Unmanned Aerial Vehicles (UAVs) have become commonly used to perform a wide range of commercial activities such as cinematography and medical supply delivery. Consequently, regulators have become interested in designing UAV Traffic Management systems (UTMs) to coordinate UAV traffic among a collection of UAV operators. One framework which has been recently proposed for a UTM system is a combinatorial auction. In this framework, airspace is modelled as a 4D grid of space-time cells. UAV operators bid on cells which collectively form paths for their UAVs. Ideally, an airspace auction should reveal information about the current price of flight paths to bidders, allowing bidders to identify and bid on a select number of paths instead of placing as many bids as possible in the hopes of stumbling on a cheap path. Revealing too much information, however, can allow bad actors to place bids which are intended not to win but to raise the price that a rival bidder must pay. We address these twin challenges with a new information revelation framework which provides bidders with wide-ranging pricing information while suppressing bad actors. We evaluate our framework on scenarios based on a Japan Aerospace Exploration Agency (JAXA) case study and find that it can scale to thousands of bids.

Nomenclature

UAS	=	Unmanned Aircraft Systems
USS	=	UAS Support Services
UTM	=	Urban Transportation Management
UAV	=	Unmanned Aircraft Vehicle
XOR	=	A disjunction of items, only one of which can be selected
ILP	=	Integer Linear Programming

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c, C	=	4D airspace cell, set of 4D cells
β_i	=	the ith bidder
$M_i := \{m_{i1}, m_{i2}, \ldots\}$	=	the set of missions that the ith bidder would like to fly
$\mu_{ij} : 2^C \to \mathbb{R}$	=	a function mapping each flight path to the value that the ith bidder would derive from executing missi
q	=	maximum value a bidder can derive from a set of cells
$A_{i,j}$	=	The set of cells allocated to a bidder i and mission $m_{i,j}$
p	=	price bidder is charged for an allocation
B, ω	=	set of bids, set of valid bids
$v_i.v(\omega)$	=	value of bid for bidder i, value for a sum of bid values
$b = (\beta, C, v)$	=	A bid tuple, consisting of a bidder, a set of cells, and a value the bidder is willing to pay
$air(C, B, X), airv(C, B, X)$	=	Winner determination function, valuation of winning bids
$cp(c, B, X), cp(C, B, X)$	=	current price of a cell, current price of a set of cells

Introduction

Recent growth in the urban aviation industry has put pressure on cities and government agencies worldwide to create rules for using urban airspace. A number of proposals for urban transportation management (UTM) have been proposed, each aimed at ensuring the safety, efficiently, security, and equity of airspace access [1].

The FAA has mandated that a UTM ecosystem is a federated traffic management system, where operators communicate with a suite of UAS support services (USS) to coordinate, execute, and manage operations, based on established and regulated procedures. Figure 1 shows a notional UTM architecture (reprinted from [2]). UTM operations can be strategically managed through planning and sharing of *operator intent information*, in the form of an operations plan, indicating the four-dimensional (4D) volume of airspace within which the operation is expected to occur. The USS offers assistance to the operators in operations planning, intent sharing, strategic and tactical deconfliction, conformance monitoring, and management of off-nominal situations. Such services improve efficiency and reduce the need for purely tactical separation management.

The federated operations concept introduces a number of challenges in distributed planning, intent sharing, and deconfliction. In the case of drone delivery, operators are often competitive, self-interested players who are reluctant to share operational intent information with other operators[3]. Furthermore, competing for prime airspace in dense urban environments may increase the urge to engage in adversarial behavior to gain advantage over others. UTM solutions to strategic federated planning and deconfliction should ensure honest behavior, fairness, while preserving operator control over its operations and a degree of privacy about providing operator intent information and expressing preferences.

These desiderata for federated UTM management neatly coincide with the properties codified by combinatorial

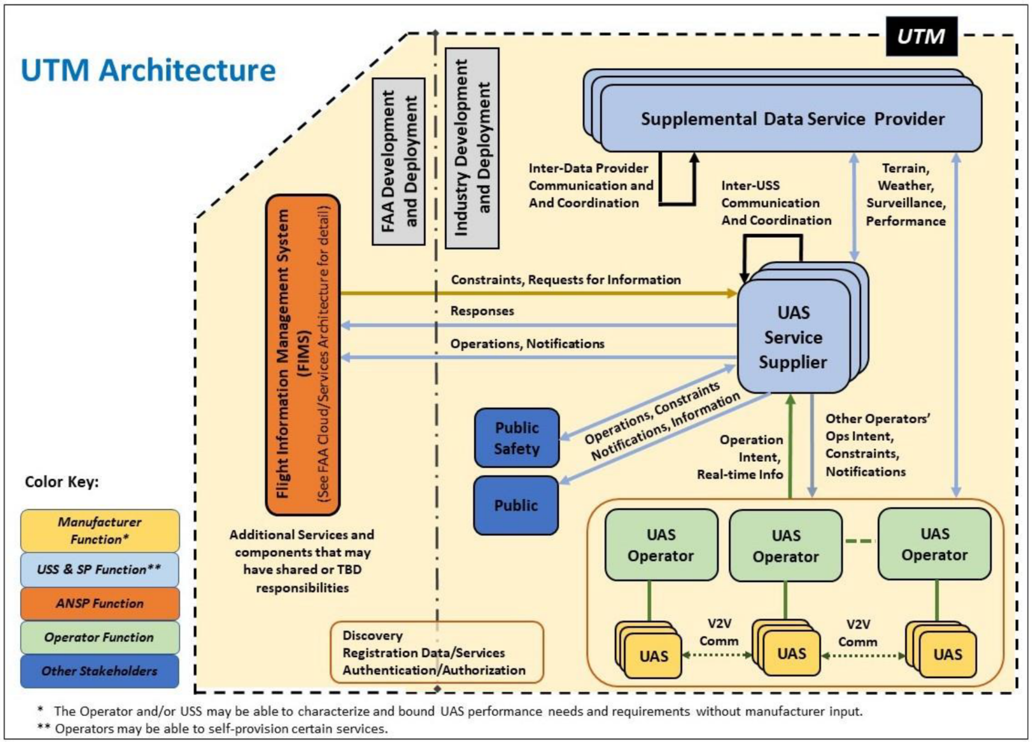

Fig. 1 Notional UTM Architecture (reprinted from [2]).

auction theory. [4]. In combinatorial auctions, a set of bidders express their preferences on packages of items, and items are then allocated efficiently to maximize total value. Such auctions have been employed for a variety of industrial applications, including transportation, and in particular UAV traffic management[5]. The primary motivation for the use of combinatorial auctions is the ability to express the 'all-or-nothing' preferences: for UTM airspace allocation, an operational intent typically has no value if it is only partially allocated.

This paper presents a framework for allocating airspace based on combinatorial auction mechanisms. Following a summary of related research, we present a set of desirable properties for an efficient, fair auction, followed by a formulation, consisting of a bidding language, a winner determination function, and a means of querying the current state of the auction. We next describe an implementation and evaluation of the the winner determination function, and a summary of future work.

Related Research

Deconfliction for UTM. Tactical deconfliction based on collisions avoidance mechanisms such as Control Barrier Functions [6, 7] or Buffered Voronoi Cells [8] have been used to reactively avoid UAV collisions. These mechanisms are dependent on UAV sensors, and may fail under adverse conditions.

The problem of Multi-Agent Path Finding (MAPF) solving for deconfliction is well studied, including highly scalable search-based MAPF solvers [9, 10] and rule-based [11] 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 [12–15]; as well as privacy protection [16]. 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) [17] has been proposed to train agents that are robust to changes in the environment.

Combinatorial Auctions. Combinatorial auctions have a long history as a mechanism for allocating public goods such as spectrum [18]. Combinatorial auctions have also been applied to other problems in transportation and delivery such as exchanging transportation requests between freight carriers [19], matching carriers and shippers [20, 21], airport time-slot allocation [22] and delivery logistics [23]. Recently, combinatorial auctions have been proposed as a framework for UTM [24]. 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 [25, 26], branch-and-bound [27], and decision-trees [28].

Desired Properties of Auctions

An airspace auction should ideally be:

(1) Incentive-Aligned. A bidder should maximize her net profit (the value of the flight paths that she wins less their cost) if she bids honestly, that is, if her bids reflect her true valuation of the flight paths that she is bidding on.

(2) Economically-Efficient. The auction should maximize the total value of the set of bids that it accepts. If all bidders bid honestly, an economically-efficient auction maximizes the overall value derived from airspace by UAV operators.

(3) Burden Minimal. A UAV operator must use the auction system to obtain a flight path for every mission that she wants to fly. Many UAV operators are small companies that cannot afford to hire an employee to engage with the auction system full-time. A UAV operator that only engages with the auction system for a few minutes per bid should nonetheless be able to obtain satisfactory results.

(4) Scalable. Airspace agencies such as JAXA estimate that even mid-size cities may see tens of thousands of drone deliveries a day by 2030 [29]. The airspace auction system should therefore scale to tens of thousands of flights.

As part of this research, we conducted a survey of San Francisco Bay Area UAS operators to elicit a ranking of airspace auction properties in terms of importance for operations. The properties deemed to be most desirable were:

- Real-Time Status Information. Real-time information about whether a bid is winning or losing.
- Price Discovery. Real-time information about flight path pricing.

- Fleet safety, collision-Avoidance.
- Burden Minimization. Being able to get optimal results without constantly monitoring the auction site.
- Fairness. Preventing a small number of bidders monopolizing airspace.
- Economic Efficiency. Maximizing the value that all operators derive from airspace.

The results of this survey informed the technical approach to the auction mechanism design applied here, which we present next.

Airspace Auction Formulation

We introduce a model for combinatorial auctions to allocate airspace to UAV operators. Such a mechanism consists of the following elements.

Airspace Model. Airspace is a 4D space with 3 space dimensions and 1 time dimension. It is modelled as a 4D grid of space-time cells. Each space-time cell represents a region of space at a particular time interval. We denote a space-time cell c and the set of all space-time cells C.

Bidders. Bidders $\beta_1 \ldots \beta_n$ correspond to UAV operators participating in an airspace auction. Each bidder β_i is associated with a set of missions $M_i := \{m_{i1}, m_{i2} \ldots\}$, 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.

Valuation function and Allocation. A bidder β_i's mission valuation functions $q_i : 2^C \to \mathbb{R}^+$, describes the maximum value that the bidder can derive from each set of cells $C' \subseteq C$. Let the set of cells A_i assigned to bidder β_i by the auction be termed bidder β_i's allocation. Let $A_{i1}, A_{i2}, \ldots$ be a partition of the allocation A_i such that mission m_{ij} is flown with flight path A_{ij}. Bidder β_i's overall valuation $q_i(A_i)$ of allocation A_i is:

$$q_i(A_i) := \max_{A_{i1}, A_{i2} \ldots} \sum_{m_{ij} \in M_i} q_{ij}(A_{ij}).$$

Let p_i be the price that bidder β_i is charged for their allocation A_i. A bidder β_i wants to maximize her net profit $q_i(A_i) - p_i$, the overall value $q_i(A_i)$ of her allocation less the price p_i that she has to pay.

Figure 2 shows the components of an airspace auction. On the left (green) a UAV operator is 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, while this auction is open, bidders can interact with it in one of four ways:

(1) Submit a New Bid.

(2) Increase the Price of a Bid.

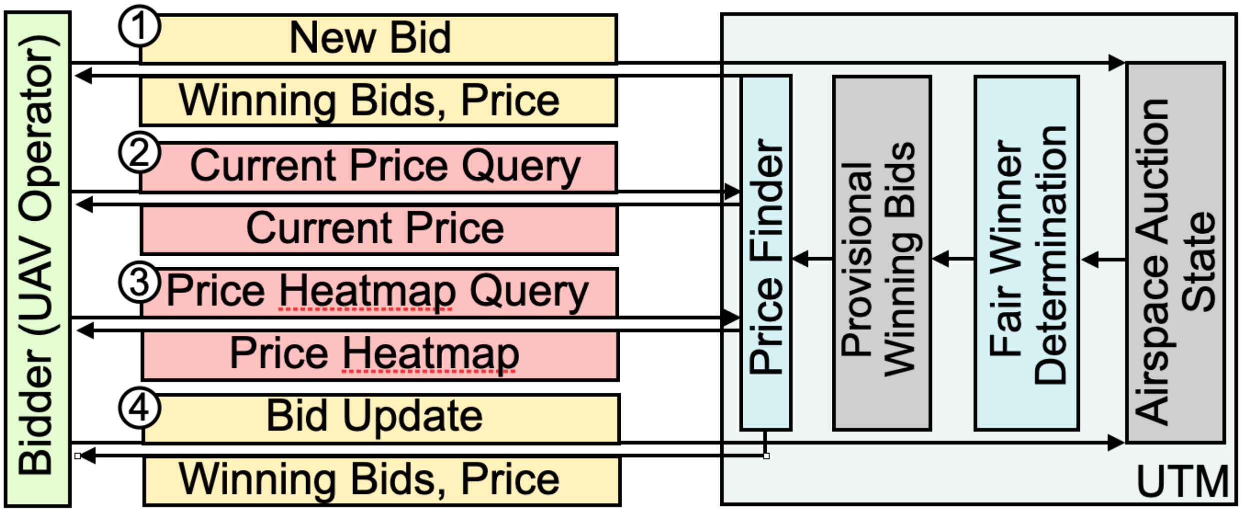

Fig. 2 The Airspace Auction Framework. Bidders (UAS operators) submit bids and queries for information to the UTM system. The UTM system stories and summarizes auction state information, and eventually generates an allocation of airspace.

(3) Query the Current Price of a Flight Path.

(4) Request a Price Heatmap for a Region of Airspace.

The following sections describe these components in more detail.

Submitting a New Bid and Increasing the Price of a Bid

We start by describing the bidding language that bidders use to submit new bids and update bids. We then describe how a provisional set of winning bids and provisional prices are generated when a new bid is submitted or a bid's price is increased.

Bidding Language. Bidders express their preferences with bids organized into XOR constraints. 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. An XOR constraint $x_j := \{b_1, b_2, \ldots\}$ is a set of bids, with the condition that at most one of the bids $b_1, b_2, \ldots$ should win. A language including XOR constraints improves the ability for bidders to specify their preferences. Specifically, XORs allow the bidder to express a willingness to take any of a set of flight paths.

Submitting and Updating Bids. A bidder places a bid b_i associated with XOR constraint x_j with the operation $\textsc{Bid}(b_i, x_j)$. If the XOR constraint x_j does not exist, it is created. A bidder increases the value of a bid $b_i := (\beta_i, C_i, v_i)$ from v_j to v_j with the operation $\textsc{IncrValue}(b_i, v_j)$. If the new value v_j is less than the old value v_i, the operation fails. A bidder β_i associates a XOR constraint with every mission $m_{ij} \in M_i$ that she would like to fly. She associates a bid b_k with XOR constraint x_j for every flight path that mission m_{ij} might take.

An Example Auction. Fig. 3 (top) shows an example airspace auction. In this auction, there are two bidders, β_1 and β_2. Bidder β_1 wishes to fly from the point s_1 in the cell $(0, 0)$ to the point g_1 in the cell $(6, 2)$. In this scenario, bidder β_1

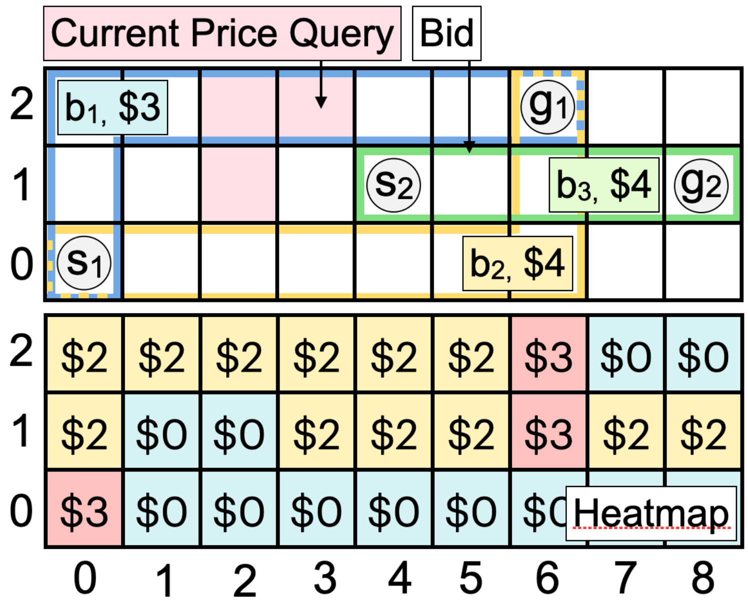

Fig. 3 (top) An example airspace auction state and (bottom) its heatmap.

would like to fly the mission with one of two flight paths:

- the flight path $(0,0) \rightarrow (0,2) \rightarrow (6,2)$, depicted in blue. Bidder β_1 values this flight path at \$3.
- the flight path $(0,0) \rightarrow (6,0) \rightarrow (6,2)$, depicted in yellow. Bidder β_1 values this flight path at \$4.

Bidder β_1 hence places the two bids inside an XOR bid $\textsc{Bid}(b_2, x_4)$:

$$b_1 := (\beta_1, \{(0,0), (0,1), \ldots, (5,2), (6,2)\}, \$3)$$

$$b_2 := (\beta_1, \{(0,0), (1,0), \ldots, (6,1), (6,2)\}, \$4)$$

We He can place these bids and this XOR statement by executing the operations $\textsc{Bid}(b_1, x_4)$, and $\textsc{Bid}(b_2, x_4)$ in any order.

Bidder β_2 wishes to fly from the point s_2 in the cell $(4,1)$ to the point g_2 in the cell $(8,1)$ using the flight path $(4,1), (5,1), \ldots (8,1)$, depicted in green. Bidder β_2 values this flight path at \$2. He therefore places the bid:

$$b_3 := (\beta_3, \{(4,1), (5,1), \ldots, (8,1)\}, \$2)$$

Auction State. Whenever a bidder either submits a new bid or increases the price of an existing bid, the airspace auction updates the auction state. The state of an auction is a 3-tuple (C, B, X) where C is the set of cells being auctioned, B is the set of submitted bids, and X is the set of submitted XOR constraints. In the example airspace auction $B = \{b_1, b_2, b_3\}$ and $X = \{x_4\}$.

Fair Winner Determination. Once the auction state is updated, a fair winner determination function $air(C', B, X)$

selects a provisional set of winning bids (Figure 2, 6-7). The set of winning bids is a maximal value, valid set of bids. We now describe what this means. A set of bids $\omega \subseteq B$ is valid if it has three properties:

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.

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

Property 3. The set of bids ω must satisfy all fairness constraints.

An example anti-monopoly fairness constraint might read *"no bidder may win more than 5% of all space-time cells"*. If ω_i is the subset of ω submitted by bidder β_i, this constraint may be expressed:

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

Since a goal of this work is to study the effects of imposing fairness on an auction mechanism, we start by developing an airspace auction with no fairness constraints, then specify 3 useful classes of fairness constraints that preserve its theoretical properties. We call an airspace auction with fairness constraints an f-Airspace Auction.

Given 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.

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

Pricing. Once we have computed an provisional set of winning bids, we compute the provisional price that every bidder has to pay for her winning bids. The airspace auction uses a Vickery-Clarke-Groves (VCG) pricing scheme, a 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.

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:

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

Response. Finally, each bidder is sent her current set of winning bids and the current price that she is being charged for them. A bidder can react to this information by placing new bids and increasing the price of her bids as long as the airspace auction is open.

Querying the Current Price of a Flight Path.

The current price of a flight path is the minimum amount of money that a bidder has to bid on the flight path to win it. Bidders will often want to inquire about the current price of a flight path before bidding on it, in order to avoid needless effort. To meet this demand, we provide a service which allows bidders to query the price of any flight. This service works as follows.

Let $cp(C', B, X)$ be the current price of a flight path $C' \subseteq C$ in an auction with state (C, B, X). We compute current prices with the expression given in Theorem 1.

Theorem 1 *If an auction is in the state (C, B, X), the current price of a flight path $C' \subseteq C$ is:*

$$airv(C, B, X) - airv(C \backslash C', B, X) + \epsilon.$$

Proof. If an auction is in the state (C, B, X), for a new bid (β_i, C', v) on flight path C' to win, the value of v plus the value $airv(C \backslash C', B, X)$ of the best set of winning bids that doesn't overlap with C' must be greater than the value of the current best set of winning bids $airv(C, B, X)$, that is:

$$airv(C \backslash C', B, X) + v > airv(C, B, X).$$

The current price of C', the minimum such value for v, is therefore $airv(C, B, X) - airv(C \backslash C', B, X) + \epsilon$. $\square$

Example Price Query. Fig. 3 (top) shows an example query on the price of the flight path $\{(2,1),(2,2),(3,2)\}$ in red. The highest price valid set of bids which don't contain these cells is $\{b_2\}$ with price \$4. The highest price valid set of bids which do contain these cells is $\{b_1, b_3\}$ with price \$7. The price of the flight path in red is therefore $\$3 + \epsilon$.

Requesting a Price Heatmap for a Region of Airspace

Ideally, the auction would allow a bidder to learn the current price of every flight path $C' \subseteq C$. Unfortunately, there are an exponential number of flight paths $C' \subseteq C$. It is therefore computationally infeasible to compute the price of every flight path. Instead, we provide a bidder with enough information to lower bound the current price of every flight path that she is allowed to know about. Knowing the lower bound of each flight path allows a bidder to rule out flight paths which are definitely out of her budget. She can then query the current price of any remaining flight path that she is interested in. We enable a bidder to lower-bound the current price of any flight path by providing a price heatmap. A price heatmap associates each cell $c \in C$ with a lower bound on the current price of any path that includes that cell.

Example Price Heatmap. Figure 3 (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.

Computing a Price Heatmap. What is a lower bound the current price of any cell $c \in C$? We claim:

Theorem 2 *For any airspace instance (C, B, X), the current price of a flight plan $C' \subseteq C$ is lower bounded by the current price of any cell $c \in C'$ in that flight path.*

$$cp(C', B, X) \geq \max_{c \in C'} cp(\{c\}, B, X).$$

We prove Theorem 2 with the following Lemma.

Lemma 3 *If flight path D' is a subset of flight path C', the current price of D' lower bounds the current price of C'.*

$$D' \subseteq C' \Rightarrow cp(D', B, X) \leq cp(C', B, X).$$

Proof. If flight path D' is a subset of flight path C', the set of cells C/D' is a superset of the set of cells C/C'. The set of valid solutions $\Omega(C/D', B, X)$ is therefore a superset of the the set of valid solutions $\Omega(C/C', B, X)$. The highest value solution in $\Omega(C/D', B, X)$ is therefore at least as large as the highest value solution in $\Omega(C/C', B, X)$, that is:

$$airv(C/D', B, X) \geq airv(C/C', B, X).$$

It follows that:

$$
\begin{aligned}
cp(D', B, X) &= airv(C, B, X) - airv(C \backslash D', B, X) + \epsilon \\
&\leq airv(C, B, X) - airv(C \backslash C', B, X) + \epsilon \\
&= cp(C', B, X). \ \square
\end{aligned}
$$

Theorem 2 follows directly from Lemma 3.

Implementation and Evaluation

The airspace auction framework was implemented and evaluated on eight UAV delivery scenarios based on a JAXA study [29]. 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.

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:

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

Code Base

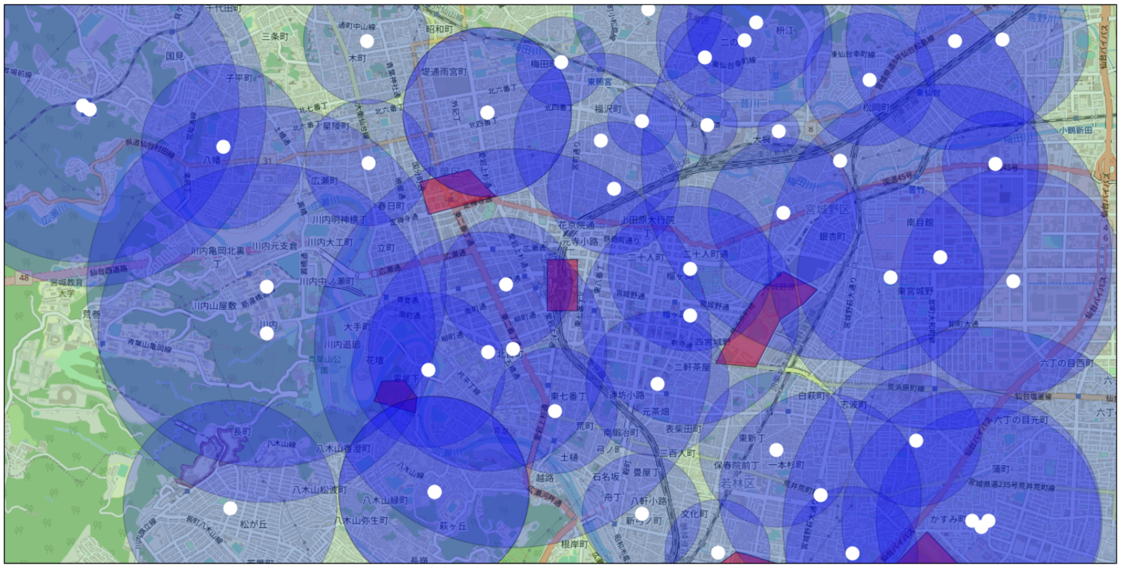

Fig. 4 A map of Sendai, Japan where drone hubs are colored white, hub delivery areas are colored blue, and no-fly-zones are colored red.

Benchmark Hardware

We implemented the fl-airspace auction as a toolchain written in Python 3.11. The ILP formulation generated by this toolchain was solved using the GurobiPy library, a Python wrapper for the Gurobi ILP solver [30]. Each evaluation was performed on a 16 core, 3.2 MHz AMD Ryzen 7 5800h CPU with a 256 KiB Li1 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.

Benchmark Scenarios

The scenarios take place 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 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 4 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 5. Gaps in the grid are depicted in black and

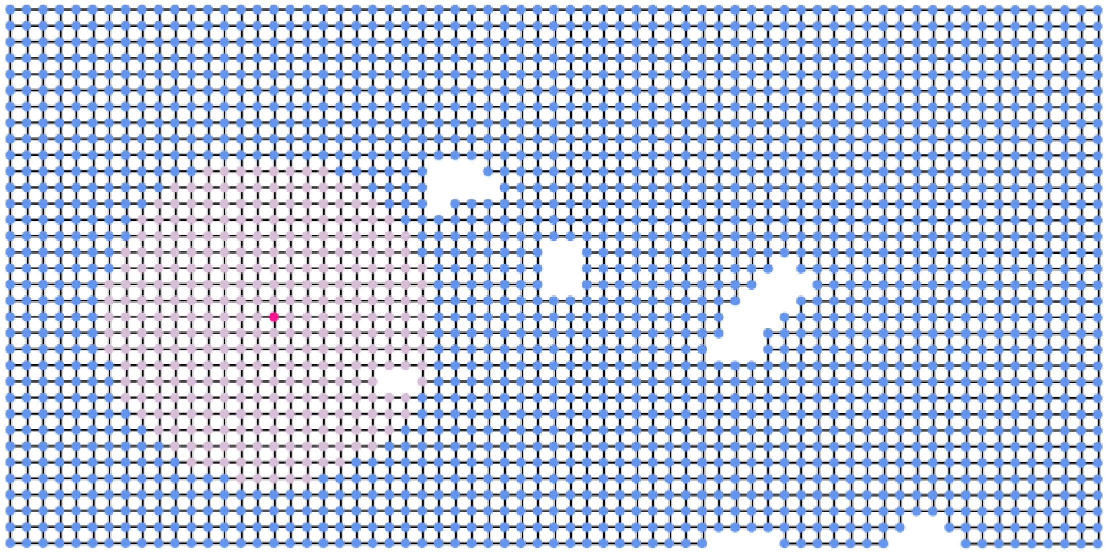

Fig. 5 The set of 150m by 150m by 150m by 3 minutes space-time cells which share a time interval. A single hub vertex is colored red. Vertices in the hub's service area are colored grey

Table 1 The time required by airspace auction and f-airspace auction to solve the winner determination problem.

Model	Cell Size (m)	Period (hr)	XOR Cn.	Bids	Cells in Bids	Airspace Runtime (sec)	f-Airspace Runtime (sec)
1	150	1	2239	7873	29046	19.3 -0.90 +0.80	44.32 -1.70 +2.2
1	150	2	4478	15603	58596	97.0 -3.45 +1.66	17.89 -0.54 +0.80
1	60	1	2239	8501	79486	109.04 -3.45 +1.66	32.69 -1.17 +0.89
2	150	1	2110	6619	22854	3.09 -0.05 +0.06	4.05 -0.10 +0.16
2	150	2	4220	13228	46696	9.54 -0.21 +0.40	11.9 -0.10 +0.10
2	150	4	8440	26421	93126	36.0 -2.10 +0.40	39.27 -0.62 +1.33
2	60	1	2110	7743	55426	6.77 -0.12 +0.10	13.17 -0.12 +0.13
2	60	2	4220	13228	46696	23.6 -1.40 +1.20	44.5 -2.79 +1.88

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 5 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 Metrice600. 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 outcome of the experiments. Each row of the table shows the hub model, the cell size, the period during which airspace is allocated, the numnber of XOR Constraints, the number of bids, the total number of cells the airspace being allocated, and the winner determination runtime for the two formulations. Each winner determination function was run 5 times on eight scenarios. The f-airspace winner determination function was run using the example fairness constraint.

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. The f-airspace auction took longer to run on the lower density scenarios due to its extra constraints but less long to run on the higher density scenarios because these constraints disallowed difficult-to-find but high value solutions. Both winner determination functions terminated in less than 2 minutes on every scenario suggesting that they are feasible on real UTM scenarios. In summary, the results strongly suggest that winner determination can be achieved for large problems in a matter of seconds, which should be reasonable in an operational setting. More experiments will be conducted to further justify this claim.

Summary and Future Work

This paper has proposed a framework for strategic deconfliction of UTM airspace based on combinatorial auction theory. Combinatorial auctions offer an efficient, safe and fair framework for allocating airspace in a federated operational environment. Future work will seek to improve the framework by planning in continuous 4D volumes using geometric constraints. We also plan to consider different ways to ensure fairness, as well and to explore ways of integrating strategic and tactical approaches to deconfliction.

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