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Pre-Flight Conflict Detection and Resolution for UAV Integration in Shared Airspace: Sendai 2030 Model Case

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ABSTRACT The increasing demand for services performed by Unmanned Aerial Vehicles (UAVs) requires the simulation of Unmanned Aircraft System Traffic Management (UTM) systems. In particular, Pre-Flight Conflict Detection and Resolution (CDR) methods need to scale to future demand levels and generate conflict-free paths for a potentially large number of UAVs before actual takeoff. However, few studies have examined realistic scenarios and the requirements for the UTM system. In this paper, we focus on the Sendai 2030 model case, a realistic projection of UAV usage for deliveries in one area in Japan. This model case considers up to 21,000 requests for Unmanned Aircraft Systems (UAS) operations over a 13 hour service time, and thus poses a challenge for the Pre-Flight CDR methods. Therefore, we propose an airspace reservation method based on 4DT (3D plus time Trajectories) and map the Pre-Flight CDR problem to a Multi-Agent Path Finding (MAPF) problem. We study first-come first-served (FCFS) and ''batch'' processing of UAS operation requests, and compare the throughput of those methods. We analyze the air traffic topology of deliveries by UAVs, and discuss several metrics to better understand the complexity of air traffic in the Sendai model case.

INDEX TERMS Unmanned aircraft system traffic management (UTM), pre-flight conflict detection and resolution (CDR), multi-agent path finding (MAPF), air traffic complexity metrics.

I. INTRODUCTION

With the emerging use of Unmanned Aerial Vehicles (UAVs) for operations such as goods delivery, surveillance, search and rescue, and agricultural monitoring, the low-altitude air traffic is expected to grow significantly in the coming years [1], [2]. Several independent UAS (Unmanned Aircraft System) Service Providers (UASSPs) will support UAS Operators to task UAVs with limited capacities to execute a variety of tasks. In particular, commercial delivery by UAVs is expected to become a widespread service. Any 'conflict' [3], i.e., possibility of collision between UAVs, must be avoided. Therefore, an Unmanned Aircraft Systems Traffic Management (UTM) system [1], [4] has to incorporate Conflict Detection and Resolution (CDR) methods.

Proposed UTM concepts have a multi-layered architecture [2] similar to Air Traffic Management (ATM) [3]. For this purpose, the International Civil Aviation Organization's (ICAO) Global Air Traffic Management Operational Concept [5] defines different conflict management or 'redundancy' layers. These layers can be separated in three categories (see Fig. 1). Each of these distinct layers are applied during the different phases of a UAV operation processing, before the UAV takes off (strategic separation), and then during its actual flight (tactical separation) [5]:

- Pre-Flight CDR methods aim to provide conflict-free paths for all UAVs before their actual takeoff.
- In-Flight CDR methods ensure separation provision for the flight paths of all UAVs during flight, to account

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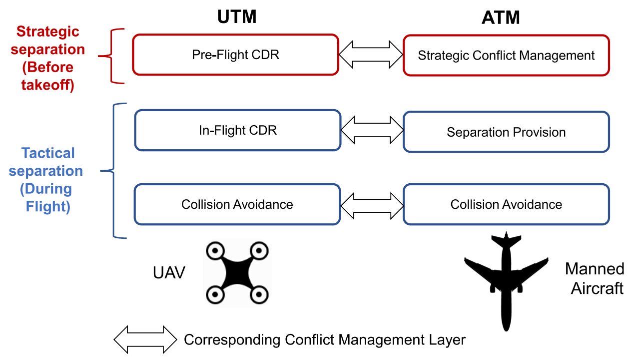


FIGURE 1. Conflict management layers in UTM and ATM.

for dynamic events such as bad weather, emergency operations, and so on.

- Collision Avoidance methods, such as Sense and Avoid, are considered as a final fail-safe and are based on sensing technology onboard a UAV.

However, unlike ATM, the conception of a comprehensive UTM system is still under discussion. First concepts of operations have been released by NASA [1], yet the design and the integration of CDR methods into the UTM system needs more investigation. While many Sense and Avoid and In-Flight CDR methods have been recently proposed and studied [6]–[11], Pre-Flight CDR methods remain mostly unexplored. Therefore, this paper will focus on Pre-Flight CDR methods and their evaluation.

In Pre-Flight CDR, which is equivalent to Strategic Conflict Management in ATM as represented in Fig. 1, the conflict detection and resolution process occurs before the given UAVs take off and fly their scheduled flight path. Therefore, in this paper, we only consider planned flight paths for UAVs and not UAVs flying in real time. Hence, Pre-Flight CDR does not include any real time considerations, i.e., surveillance issues and data communication from UAVs. These considerations belong to the In-Flight CDR phase which occurs after the Pre-Flight CDR phase, once UAVs take off and fly their flight plan. In In-Flight CDR, real-time requirements are important to effectively provide conflict detection and resolution maneuvers by In-Flight CDR methods in case of unexpected changes to the flight trajectories.

In [12], we proposed to model the Pre-Flight CDR problem as a Multi-Agent Path Finding (MAPF) problem. In MAPF, agents must avoid collisions while following paths with given waypoints in space and time from given start locations to goal locations. However, the standard MAPF setting is limited and not directly applicable to the UTM domain. For instance, the standard formulation describes a "one-shot" problem, where all agents start simultaneously and all have a distinct pair of start and goal locations. It also assumes homogeneous agents that all have the same size, are contained inside cells of the given grid map, and all move by one cell at each time step. So we included heterogeneous agents and ongoing UAV operations processing in the formulation of the MAPF problem. In this paper, in addition to the extension of the MAPF model formulation to Pre-Flight CDR, we conduct a deeper investigation into the Sendai model case and formulate a set of metrics to analyze the complexity of low-altitude air traffic.

This paper makes the following main contributions.

- We analyze the necessity for advanced Pre-Flight CDR methods in future UTM systems. This necessity is motivated by the characteristics of the Sendai 2030 model case and an empirical comparison of 3D and 4DT (3D plus time Trajectories) airspace reservation methods.
- We present new results regarding the throughput of first-come first-served (FCFS) and "batch" processing based methods for Pre-Flight CDR.
- We characterize and analyze the UAV traffic topology for deliveries by UAVs and suggest several metrics to understand the complexity of air traffic in our model case.

The rest of the paper is structured as follows. Section II presents related works. Section III motivates the importance of advanced Pre-Flight CDR methods. Then, Section IV formulates the Pre-Flight CDR problem as MAPF problem. Section V analyzes the UAV traffic topology of our model case. Section VI introduces our set of metrics to assess air traffic complexity. Section VII explains our simulations and their experimental results. Section VIII summarizes and concludes the paper.

II. RELATED WORKS

A. CONFLICT DETECTION AND RESOLUTION METHODS AND METRICS

In the ATM domain, extensive studies have been conducted for the conception and integration of CDR methods to all safety layers [3]. Differently, since UAVs have distinct capabilities, there are different challenges in the design of a UTM architecture. Following NASA's initiative [4], there currently exist several studies and works on the conception of a UTM system to enable the safe integration of UAVs in low-altitude shared airspace. Most of these works address the integration of In-Flight CDR methods [7], [11] or Sense and Avoid methods [6], [13], [14].

[2] introduce a multi-layered architecture based on a taxonomy for CDR, but they mainly address the conception of the In-Flight phase [15], which is assessed through Monte Carlo simulations. Also, the conception and evaluation of In-Flight CDR methods with simulations based on real world scenarios is discussed in [10], [11]. [16] introduce 4DT (3D plus time Trajectories) into UAV trajectory modeling, and they focus on the uncertainties and technical errors in UAV navigation. However, none of these works have presented practical methods to proactively de-conflict UAV traffic before the UAVs take off, i.e., Pre-Flight CDR methods.

By contrast, high altitude air traffic is already well analyzed, and ATM systems have been deployed for years [17]. In the evaluation of ATM systems, a variety of metrics have been proposed to characterize the complexity of air traffic. However, due to the presence of air traffic controllers and

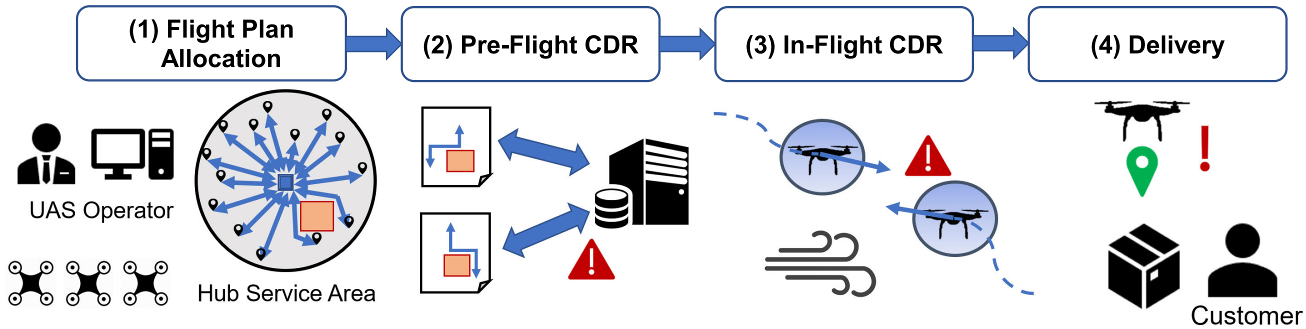


FIGURE 2. Flowchart of the different steps from operation request submission to delivery. (1) Operations requests are submitted by each independent UASSP; (2) Conflicts between all operations are solved in the Pre-Flight CDR phase which is the focus of this paper; (3) When en-route, conflicts between flying UAVs can be solved with In-Flight CDR in case of dynamic events occurring; (4) A UAV reaches its delivery location, and returns to its hub afterwards.

pilots, these studies mostly rely on human workload as one of the defining factors of traffic complexity [18]–[20].

However, in the UTM context, new metrics must be defined to meet the challenges of increased automation and new traffic patterns. Studies on the predicted low-altitude air traffic are very recent. In particular, [21] proposed metrics to assess the density of the predicted low-altitude air traffic in Paris. Nevertheless, their study is focusing only on the In-Flight CDR situation. Further, their simulation scenarios are randomized traffic patterns that do not realistically represent the situation of deliveries by UAVs.

B. MULTI-AGENT PATH FINDING

The Multi-Agent Path Finding (MAPF) problem has been mainly studied without real world deployment considerations, with many works proposing approaches to solve instances for 2D video game benchmarks [22], [23]. In the MAPF setting, agents located in a graph must move according to the given graph representation to their goal locations without colliding with each other for each move. However, new directions were established recently to handle complex real-world scenarios, such as robot path finding in Amazon Robotics warehouses [24], [25]. Here, agents are split into groups and a set of tasks is given to each group [26], [27]. The objective is to allocate tasks to each agent while providing conflict-free paths.

[24] introduce a decentralized approach and focus on ongoing task allocation. In the UTM context, we assume that every agent is assigned a given start and goal location. So, we do not consider the task allocation process in our work.

[28] also propose an online version of MAPF solvers, where agents can replan their paths to solve conflicts when new agents appear. In our context, we do not allow replanning of previously generated paths in the pre-flight phase for practical reasons, i.e., UAS operations that are accepted cannot be modified anymore, and since UAVs may belong to different UASSPs, this would potentially impact several UASSPs.

III. THE NEED FOR ADVANCED PRE-FLIGHT CONFLICT DETECTION AND RESOLUTION METHODS

UAS Operators will use UAS Service Providers (UASSPs) to integrate UAS operations into low-altitude airspace, which is shared among several independent UASSPs. Unlike the human-centered ATM system, the UTM system is an automated system that must ensure conflict-free paths for a large number of UAVs, with the steps depicted in Fig. 2, UAVs will be tasked to perform deliveries anytime during a day.

To demonstrate the need for advanced Pre-Flight CDR methods, we first introduce the Sendai 2030 model case as a realistic scenario of future deliveries by UAVs and the representations considered in our study. Then, we motivate the necessity of Trajectory Based Operations (TBO) to handle the expected scale of UAS operations requests.

A. SENDAI 2030 MODEL CASE

This section describes the Sendai 2030 model case, which is based on a study that aims to project UAV service demand in 2030 in Sendai, Japan. The study was conducted by a consulting company, as part of the NEDO UTM Project, a large-scale governmental project on designing, simulating and specifying the UTM system.

The dimensions of the considered area in the given region are of 14.35 km×17.10 km. The study specifies that UAVs are allowed to fly between 90 m and 150 m, relative to the elevation of the terrain, hence, there is a 60 m altitude range.

The scenarios considered by this study are delivery services provided by UAVs that fly from hubs locations to designated service locations. The study considers three major logistics companies (hereby anonymized as A, B and C, see Table 1) that provide deliveries of goods such as mail and package delivery, as well as a Red Cross blood center D which collects blood samples between medical centers.

The different hubs locations are set by the study considering the expected demand in the area. The assignment of the service locations is assumed to be done independently by UAS Operators within a given service radius around a hub.

Figure 3 depicts positions of hubs and their associated service area with a different color for each company.

We distinguish two types of deliveries (see Table 1 for concrete values derived from the study of the consulting firm).

- *Hub-to-Home*: deliveries performed from hubs to service locations (homes) located within a given service

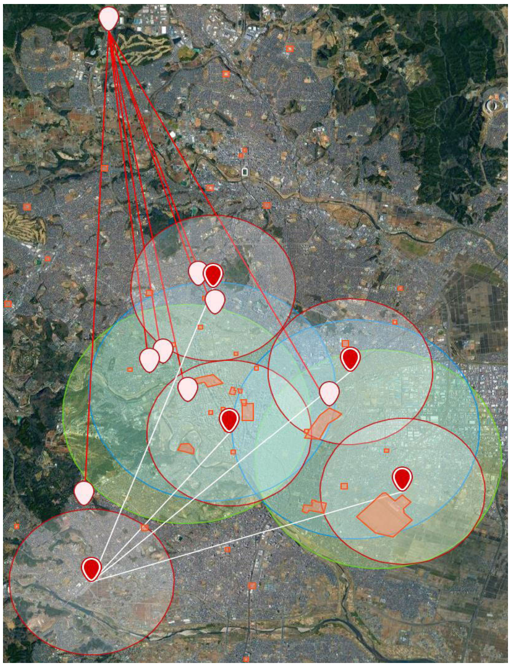


FIGURE 3. Map of Sendai, Japan, including candidate hub locations and service areas (circles). The white and red icons indicate the hub locations for Hub-to-Hub operations for company C and D respectively.

TABLE 1. Parameters in the Sendai 2030 model case.

Type of delivery	Company	#Hubs	Vicinity radius	# Deliveries per day
Hub-to-Home	A	2	3000 m	6,578 – 9,866
	B	2	3000 m	4,385 – 6,578
	C	5	2000 m	2,192 – 3,289
Hub-to-Hub	C	5 (1 main hub)	-	747 – 1,494
	D	8 (1 main hub)	-	8

radius. Inside these areas, we fix the minimum flight path length to 300 m.

- *Hub-to-Hub*: deliveries performed between given pairs of hubs only.

The study estimates that, by 2030, the UAVs performing these delivery services will be able to carry up to 5.5 kg of payload, fly at 23 m/s maximum horizontal speed, ascend at 10 m/s and descend at 3 m/s. The expected operation time is 27 minutes.

In this study, one day of delivery service represents 13 hours, from 8 am to 9 pm. According to customers' demand in the region, weight of deliveries, and expected capabilities of UAVs, the study estimated that there is a total demand of up to 13,910 operations per day in normal season and up to 21,235 operations per day in busy season considering the given companies altogether.[1]

In this paper, we assume that each of the given companies uses its own UASSP.

B. MAP AND UAV REPRESENTATION

The representation of our space is a 3D grid map composed of cells with 30 meters edge length. Thus, according to the Sendai model case area dimensions, we consider a 3D grid map of dimensions 478×570 cells, which is delimited in altitude by a 2 cells range (60 m range) relative to the elevation. The positions of static obstacles, i.e., blocked cells, is fixed according to the given elevation map of the region and there are 41 distinct no-fly zones fixed by the study.

[1] UAS reliability and risk assessment safety were not included in the survey provided by the consulting firm.

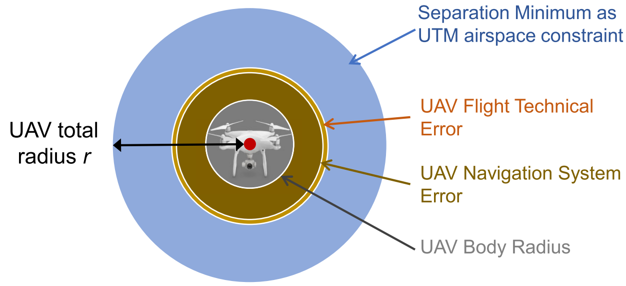


FIGURE 4. The different layers considered in the accumulated radius *r* for each UAV.

We consider quadcopter UAVs that have holonomic motion, and can move in any direction at any time, or hover. In CDR, each UAV is conceived as a sphere of "total" radius r, which is composed of several layers as shown in Fig. 4 and Eq. 2, including the physical size of the UAV *BodyRadius*, the UAV navigation system error *NSE* (i.e. uncertainty in actual position), UAV flight technical error *FTE* (i.e. uncertainty in deviation from straight line of flight), and the separation minimum *SeparationMinimum* defined by the UTM regulator. As in ATM, these parameters relate to operational risk [29].

$$Constructor = BodyRadius + NSE + FTE \quad (1)$$

$$r = Constructor + 0.5 \cdot SeparationMinimum \quad (2)$$

Although we do not consider the precise kinematics to model each UAV trajectory, our simulations are hereby informed by real-world data provided by the study. The study provided different existing UAVs specs in the Sendai 2030 Model Case such as wind stability, range, payload, and autonomy. The reliability of these parameters has been tested in real world experiments with experimental flight tests. With these real-world data, we determined the different accumulated radii values r for each considered UAV, and thus we hereby consider values ranging from 15 m to 30 m.

C. CDR ASSESSMENT

Next, we want to estimate the number of conflicts that would have to be handled by an In-Flight CDR method, if no Pre-Flight CDR is applied.

Each agent is represented by a sphere of given radius r_i, and a center position p_i. To avoid a conflict, we need to prevent any violation of the minimum separation distance between two agents a_i and a_j, i.e., the sum of their respective radii, $r_i + r_j$. Hence, we define the following constraint to ensure there is no conflict:

$$\forall t, dist(p_i(t), p_j(t)) > r_i + r_j \quad (3)$$

The following study calculates the frequency of conflicts in the Sendai 2030 model case, assuming no conflict resolution

TABLE 2. Number of conflicts in two instances of simulating deliveries in the Sendai 2030 model case.

# Operations	20,681	17,935
# Conflicts	17,124	14,183
Average # Conflicts per Operation	0.828	0.790
2-way Conflicts (% of the total #)	16,705 (97.55%)	13,804 (97.33%)
3-way Conflicts (% of the total #)	417 (2.44%)	377 (2.66%)
4-way Conflicts (% of the total #)	2 (0.01%)	2 (0.01%)

is applied. We assume that each UAV has a total radius set to 30 m. Table 2 shows that a high number of conflicts occur for different numbers of operations submitted during a 13 hours service day, assuming no CDR methods are applied. Figure 5 visualizes the distribution of conflicts for a simulated instance of 19,573 operations submitted during one day.

We observe that more than 80% of the reported conflicts occur "enroute" (during flight), i.e., at least 50 m away from the takeoff/landing location or delivery location. Hence, an In-Flight CDR method would need to be frequently activated to handle the conflicts. Therefore, Pre-Flight CDR methods are an important "redundancy" layer to ensure the safety of the airspace.

Moreover, we analyzed the number of UAVs involved in the same conflict, from two to four UAVs (see Table 2). The majority of conflicts involve two UAVs, which can be seen as simple case of pairwise resolution. However, there is a non negligible number of 3-way and even 4-way conflicts, which would require more complex resolution methods.

D. TRAJECTORY BASED OPERATIONS CONCEPT

In the new generation of ATM systems, the concept of Trajectory Based Operations (TBO) is expected to be deployed [30]. TBO consists of a coordination of four dimensional (3D plus time) trajectory (4DT) predictions and executions, whereby an aerial vehicle must follow given waypoints in space and time. With this "strategic 4D trajectory de-confliction" [30], TBO is expected to reduce air traffic complexity, by reducing the number of conflicts to be solved tactically, i.e. during flight, and its efficiency has been assessed independently in recent works [31], [32].

Similarly, in the proposed strategic deconfliction phase for UTM, our Pre-Flight CDR method solves conflicts between operations before the associated UAVs take off.

We hereby assume that Pre-Flight CDR is performed by a central entity which receives the operations of multiple UAS Service Providers (UASSPs). Since the Pre-Flight CDR process occurs before the given UAVs take off, whereby conflicts are predicted and resolved relying on 4DT, surveillance functions are not included in this phase as UAVs are not actually flying in this step. Once the predicted conflicts are solved, the central entity communicates the modified 4D trajectories to the UASSPs, which transmit the flight plans to their respective UAS Operators. In the Pre-Flight CDR phase the efficiency of the communication medium is not critical, and we hereby assume that communication is done via Internet as described by NASA UTM [33].

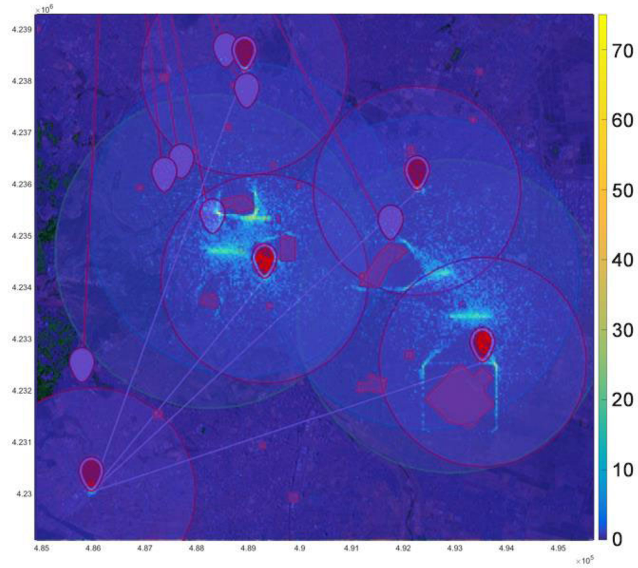


FIGURE 5. Visualization of the distribution of conflicts in the Sendai 2030 model case. Brighter points have more conflicts.

In the conception of the pre-flight phase for an UTM system, we will assess the efficiency of the 4DT paradigm in comparison to simpler options such as the use of 3D trajectory reservation.

Figure 6 shows the concept of 4DT and 3D conflict detection (CD). With 3D trajectory reservation, the entire trajectory of each UAV is considered as a spatial obstacle for other operations during its entire flight duration.

Next, we assess the effectiveness and practicality of the use of 4DT and 3D trajectory reservation in terms of the number of UAS operations rejected, which is an important practical consideration for the UTM system (see Fig. 7). We hereby use a simple first-come first-served (FCFS) approach, implemented by the Cooperative A* (CA*) algorithm [34], to plan all UAS operation requests in the simulations. Considering a 1 hour time window in normal and busy season in the Sendai 2030 model case, the percentage of rejected operations is significantly higher when using 3D trajectory reservation than 4DT in both CD (no resolution) and CDR cases, as the reserved trajectories occupy more space in an inefficient manner as there is not necessarily an actual conflict as shown in Fig.6 a).

4DT CD is also impractical as it rejects almost 50% of the operations, and the UAS Operator has to resubmit every other UAS operation. In contrast, 4DT CDR presents a very low rejection rate, whereby we observed that most of the rejected operations are due to conflicts that occur close to hubs.

IV. PRE-FLIGHT CDR AS A MAPF PROBLEM

First, we define the Multi-Agent Path Finding (MAPF) problem for Pre-Flight CDR. Then we discuss strategies to handle ongoing processing of UAV operation requests.

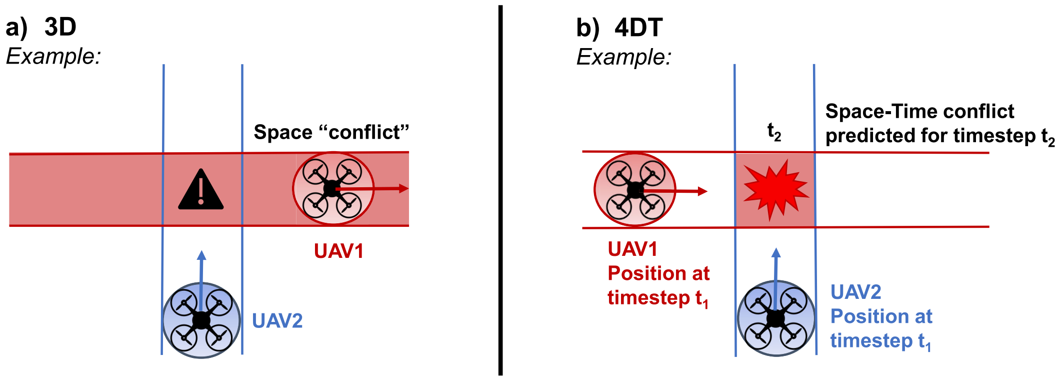


FIGURE 6. Examples of conflict detection (CD) in 2D for clarity of the representation: a) in 3D, in this example, UAV1 and UAV2 flight paths intersect spatially but there is no actual conflict, and the entire flight path of UAV1 is considered as an obstacle for UAV2; b) in 4DT, in this example, an actual conflict is detected between UAV1 and UAV2 flight paths in 4DT, as UAV1 and UAV2 cannot be at the same location at the same time.

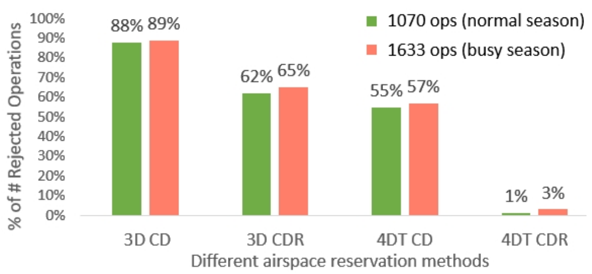


FIGURE 7. Percentage of rejected UAS operations for each airspace reservation method.

A. PRE-FLIGHT CDR PROBLEM MODEL

A MAPF problem can be extended to a Pre-flight CDR problem as follows: An instance of our problem is composed of N operations $O = \{O_1, \ldots, O_N\}$, which are performed by agents (UAVs), and an undirected graph $G = (V, E)$, which is a 26-neighbor cubic grid allowing diagonal moves. Agents can 'move' along an edge of G or can 'wait' on a vertex of G. An agent a_i assigned to perform O_i is characterized by:

- A *radius* r_i: as in Sect. III-A;
- A *speed* sp_i: the given speed of a_i is considered uniform on the whole path. In the UTM context, this would be a constraint to ensure conflict-free paths generation [16];
- A *start* s_i and *goal* g_i location: an operation O_i is composed of a pair of paths, an outbound path and a return path. The outbound path leads from a hub location s_i to a delivery location g_i, and the return path is assumed to be symmetrical to the outbound path. We assume a fixed duration δ_i for the duration between when a UAV lands to deliver some good and start returning to its hub location;
- A *start time* $t_i^s > 0$: the time at which the operation must start, hence when the agent takes off.

In the UTM context, we define the altitude constraints for any given point in space of coordinates (x, y, z) and which belongs to the path of an operation as:

$$elev(x, y) + alt_{min} \leq z \leq elev(x, y) + alt_{max} \quad (4)$$

With $elevation(x, y)$ the elevation value of the point of coordinates (x, y) in a path, and alt_{min} and alt_{max} the fixed altitude bounds.

Moreover, since each agent's delivery operation includes an outbound path and a return path, we must ensure that the precedence relation between the outbound path and the return path is satisfied.

In the UTM context, low-altitude airspace is often seen as a common resource shared among cooperative agents that would accept any deviation from their initial path to minimize the overall air traffic. Thus, the objective we hereby adopt remains the same as in standard MAPF, i.e., to minimize the sum of individual costs: min $\sum_{O_i \in O} T_i$, with T_i the total cost of the operation O_i, which is the total distance or the total duration of an operation. A solution consists of conflict-free paths for all N operations such that no violation of minimum separation occurs.

Unlike high altitude airplanes, UAVs come in a wide variety of different sizes, speeds, kinematics and so on. We consider "heterogeneous" UAVs with different sizes and speeds, whereby speeds range from 15m/s to 18m/s and sizes range from 15m to 30m. Here, we only consider quadcopters which are holonomic agents, and thus can directly follow any given trajectory without particular motion constraints. Hence, the precise integration of kinematics is not in the scope of this paper. To address heterogeneous agents, our conflict detection process based on the computation of a Time To Collision (TTC) [12], [35] allows to accurately detect conflicts between UAVs of different sizes and speeds by considering their 4D trajectories. We incorporated geometrical computations [12], [35] into A*-based MAPF solvers such as Enhanced Conflict Based Search (ECBS) and Cooperative A*. Moreover, in the conflict detection step, we apply a spatio-temporal pruning to filter out operations that may not overlap in flight times or may not intersect spatially.

As described in Section I, in the Pre-Flight CDR phase, the conflict detection computations are performed considering the whole flight plans of UAVs before takeoff. Thus, there are no real time requirements for the computations of conflict detection in Pre-Flight CDR, unlike In-Flight CDR methods where such computing issue would be critical.

B. ONGOING PROCESSING OF UAS OPERATION REQUESTS

With the steps depicted in Fig. 2, UAVs in the Sendai 2030 model case are tasked to perform deliveries anytime during the day. This requires ongoing processing of UAS operation requests.

We present two strategies to process incoming requests for UAV operation: (1) first-come first-served (FCFS) processing and (2) batch processing. For FCFS processing, we adapt the Cooperative A* algorithm [34]. For batch processing, we adapt the Enhanced Conflict Based Search (ECBS) algorithm [36], which is a state-of-the-art MAPF solver.

FCFS Processing with Cooperative A*: A simple baseline approach commonly adopted in traffic management is the use of first-come first-served (FCFS) processing. Here, every time an operation is submitted, it is processed in the order of arrival, while previously processed operations are considered as spatio-temporal obstacles for later operations. This is equivalent to the concept of the Cooperative A* method that uses a reservation table for each given agent planned in order [34]. This type of approach is proven to be unbounded sub-optimal (the solution cost can be very far from the optimal) and incomplete (a solution might not be found even though it exists).

Batch Processing with ECBS Algorithm: Batch processing has been shown useful in domains such as in data processing [37].

Let us assume our problem starts with an empty airspace and a first MAPF instance contains a set of UAS operations. So, the first MAPF instance is always a "one-shot" instance. Then, while the agents execute their generated plan, a new set of UAS operations appears that might be in conflict with the already accepted UAS operations. We refer to each given set of UAS operations as a *batch* B_i that contains a certain number of delivery operations.

Hence, two types of conflicts can occur for an agent from a later batch. It can be in conflict with another operation (1) from the previous batch or (2) from the same batch.

(1) Since we assume that previously accepted operations cannot be modified, we consider the paths of these operations as spatio-temporal obstacles. So, a first step of detecting and solving these type of conflicts is performed, and the existing spatio-temporal obstacles are considered when replanning for conflicts in (2).
(2) ECBS considers conflicts between agents of the same batch and solves conflicts between them.

ECBS is complete and suboptimal within a fixed bound w with respect to the sum of individual costs. More details on the functioning of the algorithm can be found in [36].

V. UAV TRAFFIC TOPOLOGY ANALYSIS

To understand the difficulty of Pre-Flight CDR encoded as a MAPF problem, we need to characterize the properties of our space. [23] note that evaluating the complexity of some MAPF instance is not straightforward.

Our environment is a 3D space where agents can change altitude while satisfying elevation constraints. The static obstacles, i.e. no-fly zones, have an occupancy of 1% of the total flyable volume of the area, but are concentrated in a smaller area of the region.

Further, we estimate that the average occupancy by UAVs at anytime is about 0.3% of the total flyable space, assuming a total separation radius of 22 m. Even though this percentage might seem quite low, the proportion of UAVs in the total flyable volume is not a sufficient metric to indicate whether an instance is dense or not. As depicted in Fig. 3, many operations are concentrated in a smaller area of the region, and the major part of the considered space is practically empty.

Our situation is different from standard MAPF problems with ground vehicles that can consider a high number of static obstacles but less agents. In particular, we can distinguish two types of ground traffic situations commonly used in the literature, notably in the MAPF field:

- *Uniform random instances.* In these instances, agents are positioned randomly in the space to produce various encounter situations. This relates to Monte Carlo simulations which aim to validate a given method by stressing the simulation conditions in repeatedly generated random samples. Thus, these instances are not meant to reflect a realistic traffic situation, but are rather a method to assess the robustness of CDR techniques. While evaluating the performance of such techniques in these conditions is important, it is also paramount to study and analyze realistic traffic scenarios. To the best of our knowledge, we are the first to propose an analysis of realistic UAV traffic patterns. In particular, for delivery use cases, the traffic topology has a specific pattern that we hereby describe unlike Monte Carlo random patterns.
- *Amazon warehouses.* In this instance, automated ground robots are tasked to navigate to inventory pods and move them from their storage locations to packing stations. Thus, a "corridor-like" traffic is induced, where agents move in limited directions in a cluttered environment.

In these 2D scenarios, the number of agents are limited and mostly uniformly distributed in space. Grids range from 8×8 to 100×100 cells for largest simulated warehouses, and the number of agents depend on the size of the warehouse that can range from just ten to a few hundreds [25], [27].

In the case of UAV air traffic, knowing the number of vehicles in the same area alone conveys only partial information on the complexity of air traffic. For example, the two patterns in Fig. 9a) have the same number of agents, but the different traffic patterns lead to an organized traffic flow with

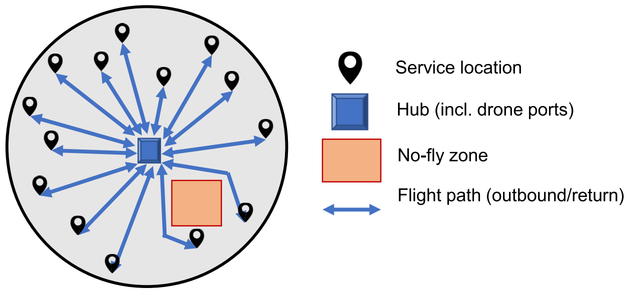


FIGURE 8. Schematic topology of UAVs' paths topology in our delivery scenario.

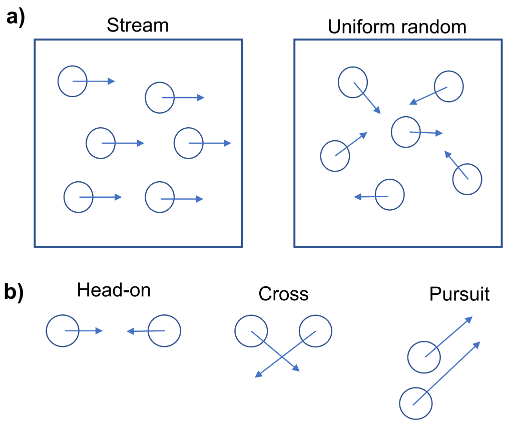


FIGURE 9. a) Different traffic patterns with same number of agents; b) Possible conflicts configurations.

no conflicts in one case (''Stream''), and to a conflict-laden situation in the other one (''Uniform random'').

Our scenario is also different from the existing benchmark scenarios for MAPF in terms of agent movement. Our use case induces a specific path topology, where UAVs are flying from the same hub location to several given service locations, as shown in Fig. 8. Thus, for each hub, we can observe a ''flower-like'' traffic pattern, where UAVs are concentrated around the same hub location, which can be a source of several conflicts.

Several hubs can have their service area overlap with each other. Therefore, we can distinguish different configurations of conflicts which can occur in our context, as shown in Fig. 9b). A *head-on* conflict can occur while one UAV is departing from a hub and another UAV is returning to the same hub. A *cross* conflict can occur when two UAVs of the same hub are tasked in intersecting paths or when the service areas of two hubs overlap, thus allowing paths to cross. A *pursuit* conflict can occur when two UAVs, either from the same hub or from two close hubs, are going in similar directions but each has a different speed.

VI. AIR TRAFFIC COMPLEXITY METRICS

The complexity and the understanding of the air traffic is fundamental for the evaluation of any manned or unmanned air traffic management system. Therefore, we describe several metrics to characterize the air traffic complexity. [21] describe metrics that rely on proximity measures between UAVs in a limited setting. Instead, we propose a richer set of metrics in the context of Pre-Flight CDR.

A. NUMBER OF UAVS IN THE AIR

We can first distinguish two metrics regarding the number of UAVs in the air: (1) the average number of UAVs in the air during a given time interval (e.g. 1 h), and (2) the average number of UAVs that are flying simultaneously at any time. Both can be seen as a first simple indicator of air traffic complexity.

B. PROXIMITY MEASURES

As previously stated, measuring the number of UAVs in the air only provides partial information on an instance complexity. Quantifying the interactions between UAVs allows for a more accurate understanding of whether an instance is more complex than another as depicted in Fig. 9. If no UAV has to change its nominal path then the complexity is low, while on the other hand, if UAVs have to constantly avoid each other, then the complexity is high. Thus, an important indicator that we hereby propose is to measure the proximity between UAVs to indicate their interactions.

[21] proposes to compute airspace density metrics by randomly selecting a UAV and computing its proximity to others at that given time step. This method aims to evaluate how frequent a UAV would have to apply the given In-Flight CDR mechanism. Their study relies on a large number of samples.

For the pre-flight case, we propose a different methodology, which does not take random snapshots. It is deterministic as we take into account the flight paths of all given UAVs. We describe and quantify how close UAVs move toward each other. These metrics indicate (1) how close the closest UAV is on average, and (2) how many UAVs are in the immediate vicinity of a UAV on average [21]. In Pre-Flight CDR, the paths are entirely projected in 4D before all UAVs depart, i.e., we already assume conflict-free paths.

Average Minimum Closing Time: This indicates how close a UAV ever gets to another UAV. For each UAV, also called ''ownship'', we compute the time of the closest point of approach t_{CPA} between the ownship and the other UAVs, and we average over all ownships:

$$t_{CPA} = \frac{(p_i(t) - p_j(t))(v_i - v_j)}{|v_i - v_j|^2} \tag{5}$$

with v_i and v_j the velocities, and p_i and p_j positions for UAVs i and j at each time step t.

Average Number of Close UAVs: For each ownship, we count the number of UAVs that have a closing time of less than 15 seconds of the ownship during its entire flight path. It indicates the number of UAVs that the given ownship gets close to during its flight. The 15 second proximity threshold is based on [21] as a reference value for different types of aircrafts.

Average Number of Close UAVs per Time Step: For each ownship, we divide the previous metric by the duration of its flight. This provides an estimate of the number of UAVs that the given ownship gets close to, at anytime.

C. NUMBER OF CONFLICTS AND MODIFIED TRAJECTORIES

First, the number of conflicts detected in a scenario is an important indicator of the complexity of air traffic. The larger the number of conflicts, the more difficult it is to compute new paths that satisfy all safety constraints. Note that for batch processing, we distinguish two types of conflicts (see Sect. IV-B). For clarity, this metric will only count the number of conflicts detected within the same batch (i.e., high level nodes in ECBS).

Second, we count the number of UAS operations that had to be replanned, thus modified from their originally submitted (nominal) flight paths, whereby one trajectory might need modification to solve multiple conflicts. Note that this measure also includes paths that were only modified because of conflicts with previously accepted operations considered as spatio-temporal obstacles.

VII. SIMULATION EXPERIMENTS

In this section, we describe our simulation experiments.

- We compare the throughput of UAS operations of "batch" processing with ECBS to FCFS (first-come first-served) processing with Cooperative A* (CA*).
- We estimate the complexity of air traffic in the Sendai 2030 model case with our proposed metrics.

All approaches are implemented in Java and run on a 3.2GHz Intel Core i7-8700 desktop with 16 GB RAM. For each experiment, we generated 30 different instances.

In the Sendai 2030 model case study, the frequency of deliveries is assumed as uniformly distributed over the 13 hours service time frame. The study does not specify when the delivery requests occur. However, we can assume "peak" times with large amounts of service requests.

A. COMPARISON OF THROUGHPUT OF UAS OPERATIONS WITH FCFS VERSUS BATCH PROCESSING

Figure 10 shows that batch processing with our adapted ECBS leads to a higher throughput, that is the number of operations processed during a fixed time interval, on average than FCFS approach based on CA*, assuming peak times with a large number of submitted operations. On the other hand, if UAS operation requests are sparse, FCFS would be more practical than having to wait for a batch to fill up.

B. RESULTS FOR AIR TRAFFIC COMPLEXITY METRICS

In this section, we present the results for air traffic complexity metrics described in Sect. VI.

1) NUMBER OF UAVS IN THE AIR

First, we estimate from the Sendai 2030 model case that the average number of UAVs flying in the airspace within a 1 hour time interval is 1070 UAVs in normal season and

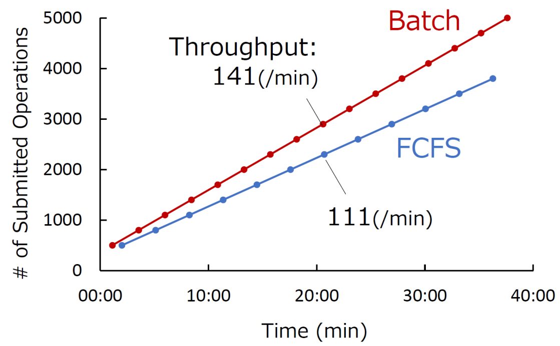


FIGURE 10. Comparison of average throughput between FCFS and Batch processing for peak times in Sendai 2030 model case.

1633 UAVs in busy season. Second, the average number of UAVs simultaneously flying at any time is estimated to be about 200 UAVs. Table 3 compares our Sendai 2030 model case to the Airbus Paris model case.

2) PROXIMITY MEASURES

The average minimum closing time becomes smaller than 15 seconds for more than 500 submitted UAS operations (see Table 4). This indicates that from this amount of submitted operations, all UAVs tend to fly closer to each other on average, and thus the traffic can be considered as dense given this threshold. The values for average number of close UAVs indicate that for 500 UAS operations submitted, a UAV flies at proximity of an average of 4 others during its entire flight path, and as expected the number of encounters increases with the number of operations. Taking into account the total duration of a flight, a UAV gets close to less than 1 other UAV on average at all times with respect to the 15 seconds threshold.

3) NUMBER OF CONFLICTS AND MODIFIED TRAJECTORIES

We start with the results on the number of conflicts. In the simulations, our adapted ECBS algorithm was used to de-conflict operations, and without loss of generalization, no previously accepted operations are considered. The UASSPs are the ones considered for each company from Sect. III-A, hence there are 4 UASSPs.

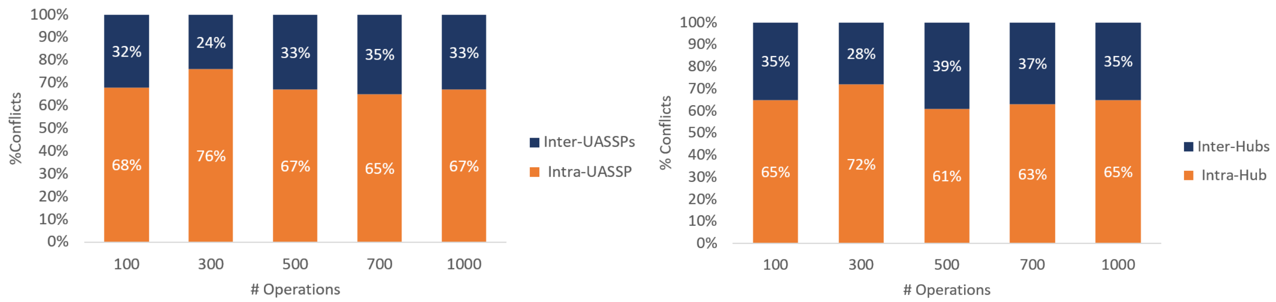
In these experiments, we aim to analyze the spatial distribution of conflicts, first, between UASSPs which have several hubs, then, between the different hubs without distinction of UASSP.

Figure 11a and Fig. 11b show that conflicts mostly occur between UAVs starting from the same hub (Inter-Hub), and thus same UASSP (Inter-UASSP). This result suggests that a "localized" use of a Pre-Flight CDR method on each UASSP level could reduce the computational effort to de-conflict UAS operations across independent UASSPs.

Table 5 shows the results for the number of modified UAS operation trajectories. First, we observe that around 50% UAS operations on average are involved in at least one conflict, so that their nominal flight path had to be modified.

TABLE 3. Comparison of the features in Paris case study [21] and Sendai 2030 model case.

Airbus Altiscope Paris Case	Sendai 2030 Model Case
In-flight case (TCAS), UAVs might need to deviate	Pre-flight case, UAVs just follow the predetermined paths
1 "ownship" considered at the center of the given area	All "ownships" considered, and average
Random snapshots at certain time steps during the simulations	Snapshots at all time steps for each flight path during the simulations, and average
Random start and goal locations, different traffic patterns: uniform random, quadrant, stream, etc.	Specific hub locations with flower-like topology, distribution of service locations in a given vicinity range
10 km × 10 km and 300 m altitude range area	14.35 km × 17.10 km and 60 m altitude range area
∼2,000 flights per hour, ∼500 UAVs anytime	∼1,000 operations (2,000 flights) per hour, ∼200 UAVs anytime



(a) Average % of conflicts for UASSPs.

(b) Average % of conflicts for Hubs.

FIGURE 11. Distribution of conflicts.

TABLE 4. Results for the proximity metrics in the Sendai 2030 model case.

# Ops submitted	Avrg minimum closing time (in seconds)	Avrg # of close UAVs	Avrg # of close UAVs per time step
100	28	0.7	0.003
300	15.5	2.1	0.007
500	12.1	3.9	0.013
1000	7.5	8.2	0.028
1500	6.2	11.7	0.053

TABLE 5. Proportion of paths modified and number of conflicts (high level nodes expanded in ECBS).

# Ops already accepted	# Ops submitted	ECBS	CA*
		# Paths modified (# High level nodes expanded)	# Paths modified
200	100	50 (14)	55
	300	146(72)	160
	500	282 (258)	339
400	100	67 (13)	67
	300	183 (70)	175
	500	344 (275)	339
700	100	80 (10)	81
	300	202 (75)	208
	500	388 (272)	399

This information can be seen as one indicator of air traffic complexity. Second, the results for ECBS and CA* are almost identical.

VIII. CONCLUSION

The development of a UTM (Unmanned Aircraft System Traffic Management) system is required to safely integrate UAVs in low-altitude airspace. UAS Operators task UAVs for different applications, such as surveillance, delivery, etc., and use UAS Service Providers (UASSPs) to avoid conflicts (possible collisions) with other UAVs. In other words, there are several independent UASSPs that share the same airspace. To avoid conflicts within one UASSP or between different UASSPs, Pre-Flight CDR (Conflict Detection and Resolution) methods play an important role in supporting the safe and efficient use of airspace. The Pre-Flight CDR phase is entirely performed before UAVs take off by considering their submitted flight plans. In this paper, we presented a novel framework for Pre-Flight CDR which is an essential phase in the conception of a UTM system. However, there exists little experience on the actual demand and properties of UAS operations in a realistic scenario. Therefore, we studied the Sendai 2030 model case, which was created by a consulting company to understand the demand for UAV deliveries in 2030. The demand reported in the study suggests that conflicts between UAVs would be very frequent and scalable CDR methods need to be developed.

Therefore, we worked on advanced methods for Pre-Flight CDR [12], [38] and In-Flight CDR [11]. Specifically, we mapped the Pre-Flight CDR problem to a MAPF (Multi-Agent Path Finding) problem, and use Enhanced Conflict Based Search (ECBS) to solve the MAPF problem. Our solution is based on the concept of Trajectory Based Operations, where each UAS operation is seen as a 4DT (3D plus time Trajectory), and UAVs become space-time obstacles for other UAVs. This concept was compared to the simpler

3D concept, where each UAS operation reserves the entire airspace needed to execute the operation. The results indicate that a simple 3D is not practical as a large number of UAS operation requests would have to be rejected.

Since we focus on deliveries by UAVs scenarios, it is important to understand the difference between our MAPF formulated problem and other MAPF problems. Occupancy by static obstacles in the Sendai model case is very low compared to other 2D problem instances. However, the model case has specific properties such as altitude constraints based on elevation and the delivery scenario induces a specific "flower-like" air traffic pattern, which is not seen in other MAPF instances.

Therefore, we defined several general metrics to study air traffic complexity, including the number of UAVs in the air, proximity measures, and the number of conflicts. At this moment, the results are hard to interpret, as comparable data is not, or only sparsely, available [21]. Our simulations also showed a localization of the conflicts within UASSPs in particular areas of the region.

We also compared two types of processing incoming UAS operation requests: first-come first-served (FCFS) processing versus "batch" processing. Although the FCFS concept seems obvious and fair, we could show that batch processing leads to higher throughput in peak times with a large number of UAS operation requests.

In our future work, we also plan to address scenarios distinct from the Sendai model case with different traffic patterns. Moreover, we plan to study the impact of a more structured air traffic with the definition of corridors.

We hope that our work on Pre-Flight Conflict Detection and Resolution can contribute to a better understanding of the management of future UAV traffic systems.

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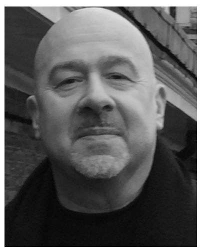

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