Report on 2nd Workshop of AI4HyDrop

Madrid, September 27th, 2024

This Project has received funding from the SESAR3 Joint Undertaking under grant agreement No. 101114805 under European Union's Horizon Europe research and innovation programme.

Abstract

As urban airspaces are expected to become increasingly complex with rising drone activity, ensuring safe, efficient, and adaptable drone operations poses significant challenges. To address these issues, the second AI4HyDrop workshop engaged expert advisory boards and SJU officers to review the project's progress and refine solutions for airspace structuring, flight planning, and drone detection.

- Airspace Structure: Emphasized preemptive planning, using reliable wind/turbulence forecasts and historical traffic data to configure airspace structures up to three days ahead. Considerations for noise and environmental impact were incorporated to align operations with urban constraints.
- Drone Flight Planning: Facilitated by a system allowing operators to submit flight preferences, which are dynamically adjusted to avoid conflicts and adhere to regulatory limits, especially over sensitive infrastructure like highways. Accurate urban models support safe navigation, while priority and fairness in authorization could maintain operational safety and efficiency.
- Drone Detection and Communication: Evaluation of current detection models highlighted the need for robust datasets, particularly in low-light scenarios. Multi-model and video-based approaches are suggested to be more effective than static images, and latency studies between detection systems and drone operators emphasized the importance of real-time communication in U-Space airspaces.

The discussion highlighted that leveraging proactive airspace design, incorporating flexible urban trajectory planning, and enhancing detection accuracy are feasible approaches to urban airspace challenges. Key takeaways include the need for human oversight in Artificial Intelligence (AI) systems, quality data inputs for consistency in detection, and collaboration among service providers to ensure seamless communication for both cooperative and non-cooperative drones. This workshop underscored AI-driven solutions with a blend of strategic planning, regulatory flexibility, and reliable communication protocols as essential for safe urban drone operations.

AI4HyDrop

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1. Introduction

1.1. Purpose and scope of the document

This workshop report presents the organization and content of the 2nd workshop of AI4HyDrop project with the advisory board members and SESAR 3 Joint Undertaking (SJU) officers. This event is part of Work Package (WP) 2 Requirements and Holistic Conceptual Framework.

1.2. Structure of the document

This document consists of seven sections and contains the following details:

- Section 1 provides the purpose and scope, as well as the structure of the report.
- Section 2 describes the framework of the workshop organization including workshop objectives, agenda, and the participants.
- Section 3 presents the solution of airspace structure that is explained in Session 1 and discussion in that session.
- Section 4 presents the solution of drone flight planning that is explained in Session 2 and discussion in that session.
- Section 5 presents the solution of drone detection and communication that is explained in Session 3 and discussion in that session.
- Section 6 summarizes the conclusions of the conducted workshop.
- Section 7 consists of the list of references used in this report.

1.3. List of Acronyms

Table 1: List of acronyms used in this report.

Term	Definition
2D	Two dimensional
3D	Three dimensional
A-FPLAS	Autonomous Flight Plan Approval Service
AI	Artificial Intelligence
AI4HyDrop	An AI-based Holistic Dynamic Framework for a safe Drone's Operations in restricted and urban areas
API	Application Programming Interface
ATC	Air Traffic Control
AWS	Amazon Web Service
BVLOS	Beyond Visual Line of Sight
CFD	Computational Fluid Dynamics
ChatGPT	Chat Generative Pre-training Transformer
CISP	Common Information Service Provider

CNN	Convolutional Neural Network
CTR	Controlled zone airspace
DCB	Demand and Capacity Balancing
DDoS	Distributed Denial of Service
DFR	Digital Flight Rule
DHMI	Devlet Hava Meydanları İşletmesi Genel Müdürlüğü
DLR	Deutsches Zentrum für Luft- und Raumfahrt
DURE	DLR U-Space Research Environment
eVTOL	Electrical Vertical Take-Off and Landing aircraft
GPS	Global Positioning System
GPU	Graphic Processing Unit
ID	Identification
INS	Inertial Navigation System
IoU	Intersection over Union
ISDEFE	Ingeniería de Sistemas para la Defensa de España
ITU	İstanbul Teknik Üniversitesi
JSON	JavaScript Object Notation
LED	Light Emitting Diode
LLM	Large Language Model
NN	Neural Network
OS	Operating System
RADAR	Radio Detection and Ranging
RAM	Random Access Memory
RF	Radio Frequency
RTTA	Reasonable Time to Act
SINTEF	Selskapet for industriell og teknisk forskning ved Norges tekniske høgskole
SJU	SESAR 3 Joint Undertaking
SORA	Specific Operations Risk Assessment
SSG	Sopra Steria Group
SVM	Support Vector Machine
SWIM	System Wide Information Management
UAV	Unmanned Aerial Vehicle
UAS	Unmanned Aerial System
UEM	Universidad Europea de Madrid
UFR	U-Space Flight Rule
USN	Universitetet i Sørøst-Norge
USSP	U-Space Service Provider
UTM	UAS Traffic Management

VLL	Very Low Levels airspace
VLOS	Visual Line of Sight
VZLU	Výzkumný a zkušební letecký ústav
WP	Work Package
YOLO	You Only Look Once

2. Workshop framework

The AI4HyDrop project organized the 2nd workshop at the European University of Madrid campus in Spain. The workshop was held on the 27th of September 2024.

2.1. Objectives

The workshop aimed to present the progress of the project and to gather inputs and advice from the advisory board members and SJU officers on the solutions of the project to ensure that the solutions are in line with the latest industrial development and development in U-space regulations.

To ensure a successful workshop and achieve the expected goals, the project outlined the following workshop objectives:

- Introduction of the project to the advisory board members.
- Presentation of the development progress of the solutions.
- Collecting input on the solutions from the advisory board members.
- Gathering feedback from SJU officers for project review requirements.

2.2. Agenda

The workshop was successfully carried out following the structure presented in Table 2. The first session was a welcome coffee and introduction where the AI4HyDrop coordinator welcomed the participants. An introductory session followed, where a brief overview of the workshop (i.e. agenda, objectives, and structure) was provided.

The workshop then proceeded with three separate sessions where the project presented its solutions with Session 1 for the airspace structure, Session 2 for drone fight plan, and Session 3 for drone detection and communication. At the end of each session's presentation, the participants were encouraged to ask questions, share their perspectives, and provide feedback. The workshop ended with a conclusion session.

Table 2: Agenda of the workshop.

Time	Activity
09:00 – 09:30	Welcome coffee and introduction
09:30 – 10:25	Session 1: Airspace structure
10:30 – 11:25	Session 2: Drone flight plan
11:30 – 12:25	Session 3: Drone detection and communication
12:30 – 12:45	Conclusions

2.3. Participants

There were 30 participants from the consortium of the project, the advisory board members, and SESAR 3 JU officers is shown in Table 3.

Table 3: List of participants.

Stakeholder Group	Organization	Number of Participants
Project Consortium	USN	2
	UEM	10
	ITU	2
	DHMI	2
	SSG	1
	VZLU	1
	DLR	1
Advisory Board	ISDEFE	1
	Indra Navia AS	1
	Kansas University	1
SESAR 3 JU	SESAR 3 JU	5
Total		30

3. Session 1: Airspace Structure

Presenter: Helene Crepin from Sopra Steria Group as part of Work Package 3.

3.1. Presentation

The first solution in AI4HyDrop project is the airspace design service. Its objective is to develop an Airspace Design Tool that will help define the optimized airspace structure on a specific day, based on the wind and turbulences, along with noise constraints.

There are 4 types of airspace structures that are considered for drone operations which are full mix, layers, zones, and tubes as shown in Figure 1.

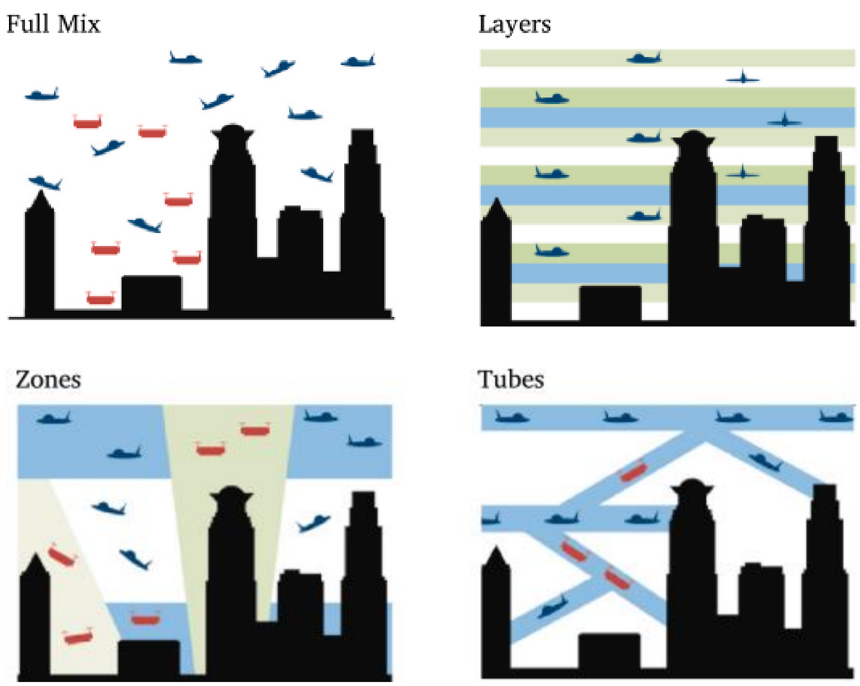


Figure 1: Type of airspace structures: Full mix, Layers, Zones, and Tubes [1].

- Full Mix
  The Full Mix airspace structure integrates all types of drone operations into a single airspace as shown in Fıgure 1. It accommodates a wide range of activities, including recreational, commercial, and emergency drone flights [2], [3]. This structure is considered as the least structured airspace which requires comprehensive management and coordination to ensure safety and efficiency amidst diverse drone activities [4]. This airspace allows for higher traffic density and more efficient routes. However, it poses to high collision risk for drones and normally does not consider social factors such as noise and pollution [1].

- Layers
  Layers airspace structure involves dividing the airspace into distinct horizontal parts, each designated for specific types of drone operations or every altitude band corresponding to the heading range as shown in Figure 1. For example, lower layers might be reserved for recreational drone flights, while higher layers are allocated for commercial or industrial drone operations. In between, there could be separated by a buffer layer [2], [5], [6], [7], [8]. This structure helps manage different types of drone activities while minimizing conflicts and ensuring safety. It is considered more structured than the full mix structure. The layer structure could reduce the probability of a collision by creating vertical separation, segregating flight according to its direction, and separating according to aircraft capabilities. This concept also produces an acceptable level of capacity while improving collision risk [1].

- Zones
  Zones airspace structure involves partitioning the airspace into discrete geographical volumes (similar to ATC sectors), with each zone having its own set of regulations and restrictions as shown in Figure 1. These zones could be based on factors such as population density, land use, airspace sensitivity, or drone characteristics. For instance, urban areas might have designated drone-free zones, while rural areas may allow for more flexible drone operations [2], [3], [9], [10], [11]. This structure provides tailored management solutions for various airspace environments. Each drone in this zone could be protected by certain volumes which size corresponds to their performance parameters such as automation, navigation, communication, and surveillance [10]. This structure could benefit from traffic separation without too advanced technology required. However, when the traffic density increases, it becomes constrained in terms of efficiency and safety since multiple aircraft are guided to the pre-set waypoints or structures [1].

- Tubes
  Tubes airspace structure creates designated aerial corridors or "tubes" for drone operations, similar to air traffic control corridors for manned aircraft as shown in Figure 1. These tubes are typically aligned along specific routes or pathways, allowing for point-to-point drone flights [1], [2], [9], [11], [12], [13]. Tubes airspace structure enables streamlined operations, particularly for long-distance or beyond visual line of sight (BVLOS) drone missions while minimizing interference with other airspace users. The tubes could also define two-way traffic lanes that are horizontally and vertically separated to avoid areas with dense populations to minimize risk [12]. This structure is considered a realistic proposal that relies on the existing technology and is supported by the authorities [1].

During the development of the solution, several key assumptions are considered such as:

- Environmental aspects. Noise impact is assessed for specific days within urban areas of low to medium density.

- Airspace structure types. Four types of airspace structures as shown in Figure 1 are considered.
- Semi-dynamic airspace design. Predefined structures are used, with adjustments possible on a day-to-day basis rather than dynamically in real-time.
- Operational scope. Only Visual Line of Sight (VLOS) and Beyond Visual Line of Sight (BVLOS) operations are considered, with no U-Space Flight Rule (UFR)/ Digital Flight Rule (DFR) usage.
- Separation method. Time-based separation is employed to manage traffic and maintain safety.

The airspace design solution involves a four-step methodology:

1. Identify Constraints: Define key operational constraints, including communication, navigation, weather conditions, Unmanned Aerial System (UAS) performance, mission requirements, and environmental factors such as noise and population density. These constraints are tailored to specific case studies to be validated. For example, a noise chart of Prague is provided in Figure 2. This step also includes defining compatible airspace structures based on these constraints, with an example shown in Figure 3.

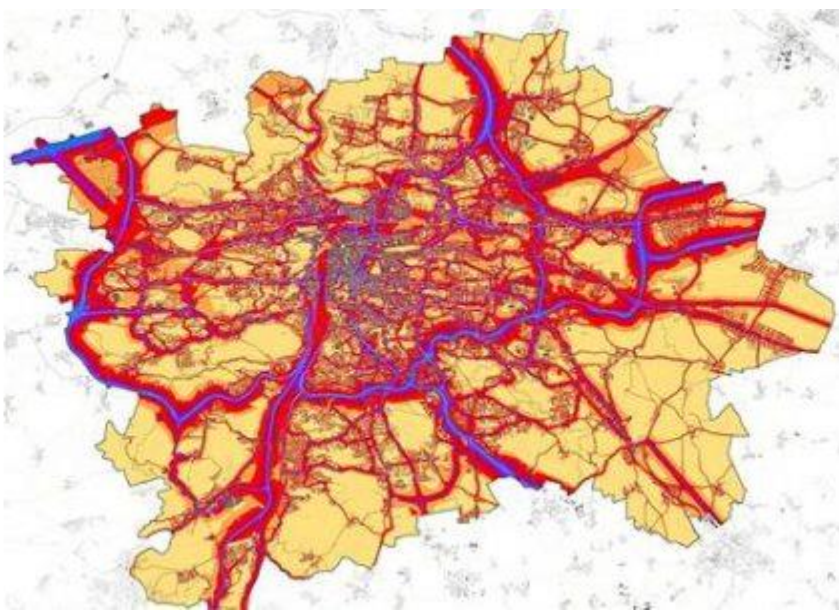


Figure 2: Example of the noise chart of Prague city [13].

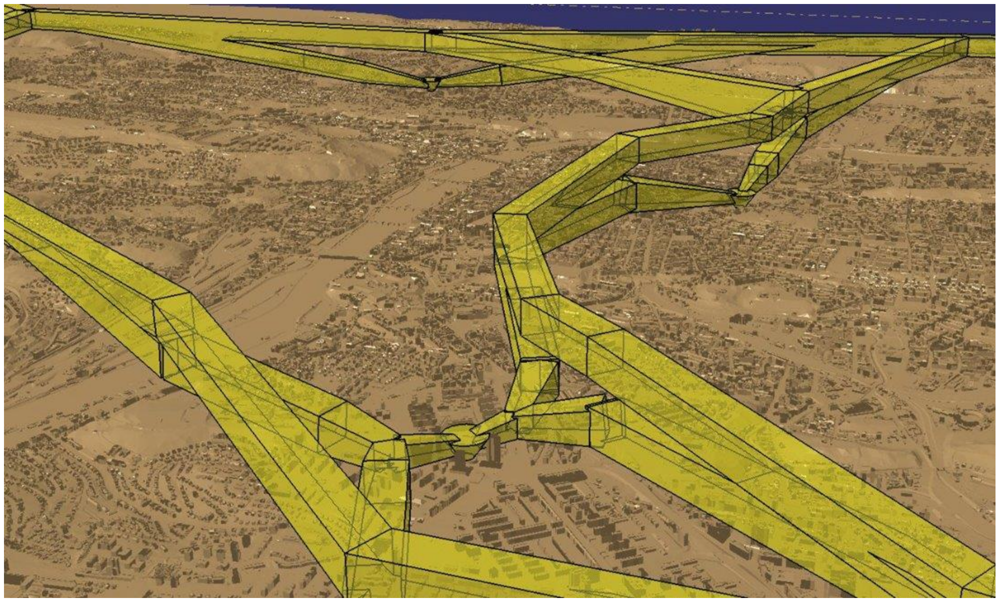


Figure 3: Example of the airspace structures.

2. Generate Drone Operations Data: Use a drone operations generator to create flight data and feed it into an AI-based model to support airspace design. Figure 4 shows an example of drone flight data.

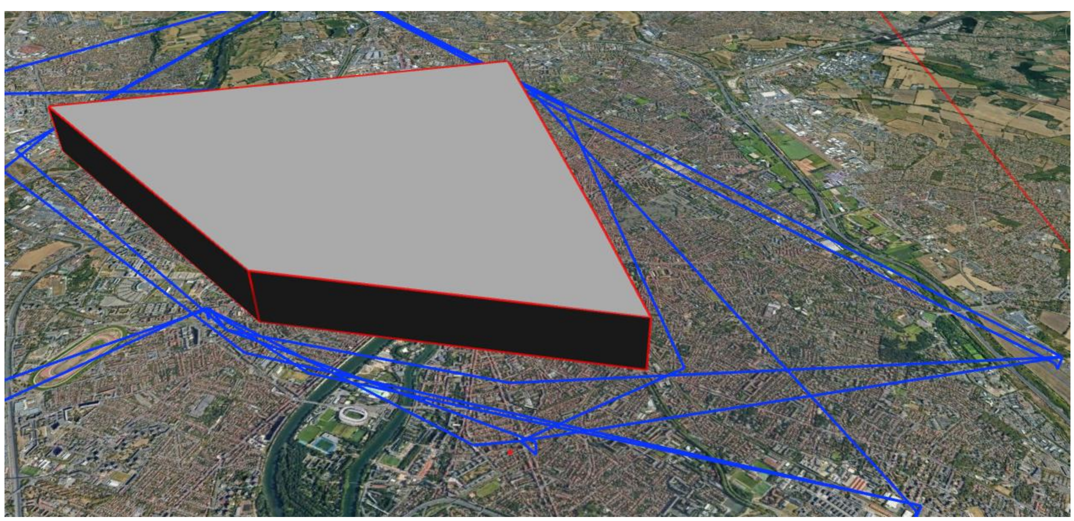
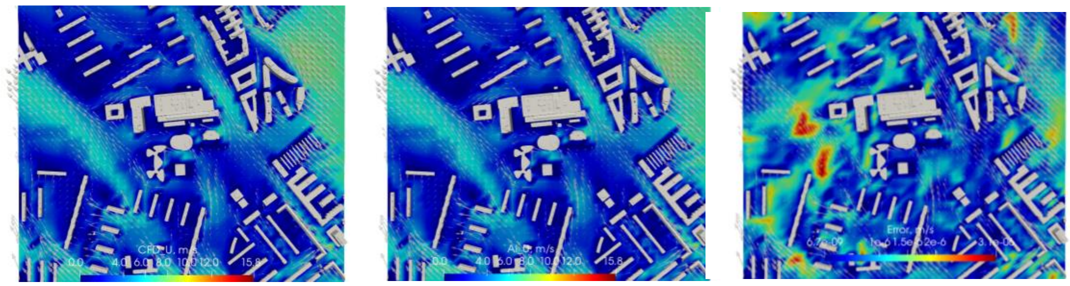


Figure 4: Visualization of drone flights data [ref].

3. Run AI Model for Wind and Turbulence: Implement an AI-based model to predict wind and turbulence for defining geo-zones. A specialized micro-scale AI wind model is being developed for Prague, based on meso-scale wind data within the city. The model focuses on Prague's main business area, where a vertiport may be located, and is trained using a database generated by 32 high-fidelity Computational Fluid Dynamics (CFD) simulations at varying wind speeds and directions. Using unsupervised machine learning, dominant spatial wind patterns are identified,

allowing the AI model to deliver rapid wind and turbulence predictions in comparison to traditional CFD models. A similar model for Oslo is currently in development. A comparison between CFD and AI model results is shown in Figure 5.



(a) (b) (c)

Figure 5: Visualization of wind and turbulence result: (a) CFD data, (b) AI model, and (c) the difference between CFD and AI model (error).

4. Activate/Deactivate Predefined Airspace Structures: Based on the constraints identified for the day, the AI model enables the activation or deactivation of predefined airspace structures. Figure 6 shows an example of an activated airspace structure.

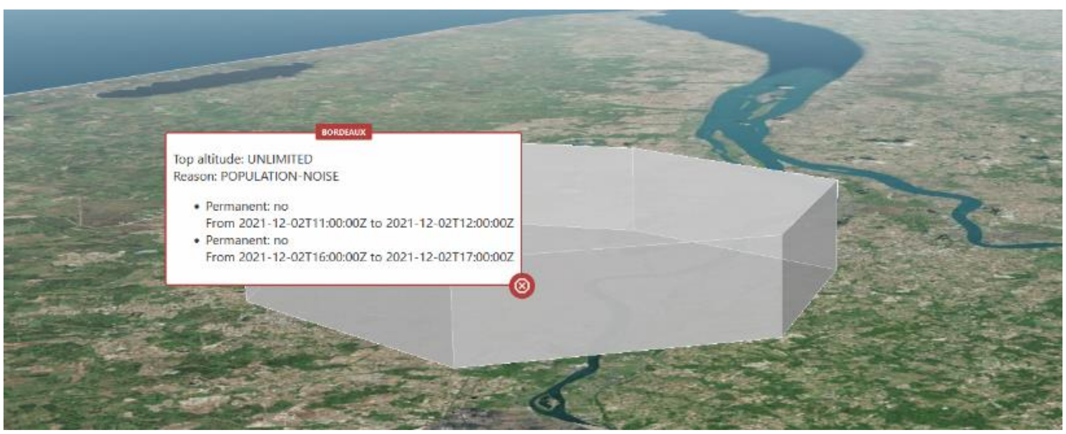


Figure 6: The example of activated airspace structure with the validation time.

At the end of the presentation, two questions are asked to the participants for their answer as an input for further development of the solution. The questions are:

- Do you see any solution to dynamically change airspace structures? Is it realistic?
- Do you think that we have forgotten any constraints?

3.2. Discussion

There are some points discussed during the presentation and at the end of the presentation between the participants and the presenter. The discussion points are:

a. Planning and Managing Drone Operations in Airspace.
Participants explored the challenges of preparing airspace structures in advance, balancing weather forecasting, drone flight plans, and other operational constraints.

The preliminary plan involves setting up airspace configurations approximately two or three days ahead, aligning with reliable weather forecasts. This approach aims to use weather data to ensure that structures accommodate drones while factoring in environmental conditions and noise constraints.

Participants also highlighted the role of historical data in estimating drone traffic. For instance, patterns, such as regular Tuesday flights, give planners an approximation of expected drone movements, especially around events like school commutes. While the system allows for last-minute flight plan submissions, flexibility is built into the airspace structure to accommodate all potential drone traffic within the planned hours of operation. This proactive yet adaptive planning is essential to ensure safe and efficient use of the airspace.

b. Role of AI in Optimizing Drone Trajectory Planning.

Participants addressed how AI-based models enhance traditional trajectory optimization methods. One participant questioned the added value of AI, noting that established trajectory optimization techniques can already handle spatial and temporal constraints effectively. While acknowledging the flexibility of conventional methods, they were curious about how AI specifically benefits this project.

In response, it was clarified that, while traditional optimization such as A* algorithm is currently used, AI's role lies in leveraging historical data to refine and dynamically adjust airspace constraints. By combining past patterns with real-time operational constraints, AI can activate or deactivate airspace structures as needed, tailoring airspace management to daily fluctuations in drone activity. This integration of AI enables a more adaptive approach, using data-driven insights to optimize drone trajectories and ensure efficient airspace utilization.

c. Adapting Drone Trajectories Based on Weather Conditions Using AI.

Participants examined how AI can adapt drone trajectories in response to changing weather conditions. A question was raised about the practical application of trajectory adjustments between points A and B, influenced by daily weather variations. Currently, the primary focus is on point-to-point (A to B) routes, where AI models predict wind and turbulence patterns to adjust these paths for optimal safety and efficiency.

To enhance route safety, an AI-based model, developed by SINTEF, quickly processes wind and turbulence forecasts for specific urban areas. Using machine learning, the model has been trained over CFD-generated datasets to predict micro-scale weather effects due to change in meso-scale wind speed and direction. By creating geo-zones that reflect hazardous or restricted conditions based on turbulence levels, the AI model can rapidly define restricted areas in real time. This enables planners to route drones around zones of high wind or turbulence, ensuring safer flights, especially for drones with lower performance capabilities that may be sensitive to adverse weather. The approach allows for the quick adaptation of routes and restricted zones, leveraging AI to enhance safety and operational flexibility in complex urban airspaces.

d. Managing Turbulence and Access in Urban Vertiports for Drone Operations.
   Participants considered the complexities of managing drone operations in urban vertiports, particularly when turbulence around buildings can impact safety. The question arose of whether drones would fly between buildings rather than above them, especially when approaching or departing from vertiports located amid high-rise structures. This setup can create significant turbulence around the vertiports, which may pose challenges for safe takeoff and landing.
   The conversation also touched on the operational impact of closing vertiports due to turbulence. While closing a vertiport may be necessary for safety, it disrupts operations and affects revenue, raising the question of responsibility. Determining who has the authority to decide on vertiport closures remains an unresolved issue, as it involves balancing safety needs with economic considerations for continuous urban drone services.
e. Impact of Urban Building Interaction on Drone Altitude and Flight Path.
   Participants examined how interactions between tall buildings can affect drone operations, even at significant heights above 100–150 feet. Research indicates that turbulence and wind patterns caused by building structures influence drone stability, not only between buildings but also at high altitudes above them. This impact is especially relevant for both high-performance and low-performance drones, which respond differently to such environmental factors.
   The conversation then focused on typical altitudes for urban drone flights, often remaining within very low levels (VLL) to align with operational standards. The appropriate altitude depends on mission requirements, such as routine A-to-B flights versus specific tasks like building inspections that may necessitate closer navigation between buildings. Mission type and drone performance levels both influence altitude and trajectory, though exact altitude standards for urban areas remain under discussion.
f. Drone Performance, Robustness, and Airspace Design Considerations.
   Participants discussed the concept of "performance" in drones, particularly focusing on how high-performance drones demonstrate robust flight control systems that help them counteract turbulence and weather effects. High robustness allows these drones to maintain their planned trajectories more closely, while low-performance drones may deviate significantly due to turbulent conditions. For example, during turbulent weather, a drone intended to follow a precise path might drift up to 180 feet off course. If the flight controller isn’t designed for robust turbulence rejection, such deviations can lead to collisions with buildings, especially during challenging maneuvers like turns.
   Further discussion highlighted how smaller drones, often used for tasks like deliveries, face added challenges in high winds due to their size, which limits their stability in adverse conditions. To ensure safe operations, airspace design is being adapted to incorporate these performance differences. For example, specific airspace "tubes" may be allocated exclusively for certain types of drones or missions,

preventing slower, smaller drones from sharing routes with larger, faster electrical Vertical Takeoff and Landing (eVTOL) aircrafts, as their different speeds and performance characteristics could lead to safety risks. This approach supports safer and more efficient urban drone operations by tailoring flight paths according to drone type and performance capabilities.

g. Urban Airspace Design, Controlled Airspace Challenges, and Drone Operations in Prague city.

Participants reviewed urban airspace management challenges and lessons from a recent trial involving medical drone operations in Prague. The conversation highlighted two primary issues: airspace structuring in cities with extensive controlled zone airspace (CTR) and regulatory constraints on urban drone operations. The entire city of Prague is covered by controlled airspace due to two airports, creating operational limitations for unmanned aerial systems (UAS) that require clearance from air traffic control. Such extensive CTR coverage often stems from historical designs in the form of cylinders or rectangular boundaries, which were implemented when airspace demand was lower. This conventional structure doesn't account for modern UAS operations, where demand for drone access is growing, especially for missions in specific urban areas. Trials in Prague and other cities, like Vienna, showed that certain CTR zones see little or no manned aviation activity, suggesting potential areas for UAS corridors that could bypass constant ATC approval.

The complexity of regulatory authorization was another key takeaway. Urban drone flights require authorization under Specific Operations Risk Assessment (SORA), especially in airspace not designated as U-space (areas planned for drone integration). Acquiring SORA approvals is complex, and urban areas impose higher safety requirements due to increased ground risk. Therefore, only drones with advanced control capabilities (i.e., "high-performance drones") may meet these standards, limiting accessible airspace for less sophisticated drones in cities.

The discussion emphasized that for efficient future urban airspace use, dynamic airspace configurations might allow temporary drone corridors within CTRs, provided they avoid manned aviation. This process could reduce the approval burden and improve operational feasibility, with the Prague trial serving as a model of the bureaucratic and logistical hurdles to address.

h. Modeling Turbulence Impact on Drone Flight Paths Near Urban Structures.

Participants discussed modeling turbulence near tall buildings to optimize urban airspace for drone operations. One participant raised the idea of analyzing turbulence effects on drones flying at different altitudes and proximity to buildings. This led to exploring the use of 2D and 3D representations for turbulence.

The primary approach under discussion is creating a 3D model that captures turbulence and wind speed around buildings. This model would allow researchers to pinpoint areas where turbulence peaks, forming "restricted" or "prohibited" zones to ensure safe drone operation. For added safety, a buffer zone would surround these high-turbulence areas, further mitigating risks as drone paths pass near the buildings. The resulting airspace visualization would show varying levels of turbulence by altitude, allowing drones to navigate more efficiently around or above turbulent areas. The use of 3D turbulence modeling could lead to more accurate urban airspace designs, providing a better assessment of optimal flight corridors based on altitude and distance from urban structures.

i. Optimizing Drone Flight Paths for Urban Noise and Ground Risk Management.
This discussion addressed the complexity of designing urban drone corridors that minimize noise pollution and ground risk while utilizing existing infrastructure. One participant noted the idea of routing drones over highways and streets to reduce noise impact but highlighted a trade-off: flying directly over roads may increase ground risk. Other projects have also explored this approach but are cautious about the heightened risk factor.
A proposed solution involves creating flight paths above rivers or other areas with fewer constraints, like populated spaces. Other participant argued that simply following roads with drones does not fully leverage their advantages unless there's a clear benefit, such as reduced travel time or accessibility beyond traditional ground vehicles.
The discussion emphasized the need for a multi-layered approach to airspace management, incorporating "tubes" (dedicated corridors), "zones" (restricted areas), and "layers" (altitude-based separations) to account for varying urban topographies and airspace demands. The hybrid system aims to balance noise, environmental constraints, and ground safety, adapting to each city's unique layout and risk profile.

j. Standardization in Drone Categories for Simplified Airspace Management.
The conversation focused on the need for standardizing drone types to streamline airspace management. One participant suggested that, in the future, limiting drone types to a few standardized categories could simplify regulation, as each category would have specific performance criteria and speed limits. This approach would be similar to vehicle regulations, where cars have set dimensions and weight limits. Standardization would reduce complexity and enable smoother integration into urban airspace systems.
Other participant added that, while industry demands may require some specialized drones for particular functions, maintaining a manageable variety in drone types is crucial. They noted that in the current project, an assessment of different drone performances has been conducted, resulting in a provisional classification of drones into three types. This segmentation allows for more manageable testing and regulation without overwhelming complexity, aiming to balance standardization with flexibility for specific operational needs.

k. Considerations for Passenger Drones and Vertiports.
The discussion centered on the operational requirements and infrastructure needs for passenger-carrying drones, specifically regarding their speed and the placement

of vertiports. One participant highlighted that for passenger drones to be viable, they must achieve a minimum speed, potentially around 100 kilometers per hour, to ensure efficiency in transporting people.

The conversation also addressed the distinct characteristics of different drone types, particularly the need to separate small drones from larger, passenger-carrying eVTOLs (electric vertical takeoff and landing aircraft). Other participant emphasized the importance of leveraging existing knowledge from the helicopter industry, noting that many operational and safety protocols for manned aviation can inform the development of eVTOLs.

The discussion raised concerns about the safety implications of integrating various drone types into shared airspace, pointing out that a collision involving a larger drone could have significantly different consequences compared to a smaller one. Acknowledging the existing literature on aviation safety, it is crucial to apply this knowledge when designing regulations and safety requirements for larger drones.

l. Selection of Airspace Structure.

The discussion delved into the complexities of establishing an effective airspace structure for drone operations, particularly focusing on the balance between safety and operational efficiency. One participant provocatively suggested considering the possibility of minimal airspace structures or even the absence of a rigid framework.

In response, the group acknowledged that decisions regarding airspace usage should be informed by historical data and operational patterns. Another participant emphasized the importance of analyzing past flight data to determine the feasibility of mixed operations on specific days. For example, if historical trends indicate only a few operations are expected, allowing a full mix of drone traffic might be appropriate to minimize disruption.

Another participant contributed to the conversation by pointing out that defining no-fly zones based on wind conditions is a necessary first step. However, transitioning from identifying dangerous areas to creating flight corridors requires a clearer rationale. They expressed concern about the abrupt shift from a safety perspective to implementing corridors without sufficient explanation.

A different speaker elaborated on the rationale behind establishing corridors, linking them to data on expected flight trajectories and historical operational data. The aim is to define safe pathways that prevent potential conflicts between drones flying at the same altitude and in close proximity.

Additionally, the discussion recognized the need for nuanced strategies based on the specific capabilities of different drone types. Another participant highlighted that some drones may be more sensitive to wind conditions, which affects their operational restrictions. Thus, while the concept of corridors serves as a useful example, the participants agreed that a more refined approach is necessary to ensure safety and efficiency in drone operations.

m. Error Computation in Wind and Turbulence Model.
   Participants engaged in a discussion about error computation in wind and turbulence model, particularly comparing the result from AI and CFD. One speaker inquired about the nature of the computation error, leading to clarification that the comparison was indeed between AI and CFD methodologies.
   Another participant mentioned that the visuals provided aimed to illustrate how AI represents computed results, which were used to train the model to ensure consistent outputs. The conversation then shifted toward understanding the relationship between real weather conditions and forecast data, with one speaker expressing uncertainty about whether the registered data included actual weather conditions or merely forecasted ones.
   The dialogue continued with questions regarding the operational parameters, particularly the implications of having a point of interest located within an urban area. Participants discussed the importance of defining alternative plans in case of disruptions, akin to protocols established in traditional aviation operations. One speaker emphasized the need for a clear definition of alternatives in operational planning to ensure safety and efficiency, especially when unexpected situations arise, such as a delivery scenario.
n. Dynamic Changes in Airspace Design.
   Participants addressed the complexities associated with dynamic changes in airspace design for drone operations. One speaker highlighted the challenges of working with dynamic changes, noting that implementing them would be particularly difficult. They encouraged the group to share ideas that could contribute to making airspace design more adaptable.
   Another participant shared their experience, describing the situation as a "nightmare," which underscored the difficulties involved. The conversation progressed to the decision made by their team to adopt a semi-dynamic approach, allowing for changes to be made two days in advance rather than in real-time due to the inherent challenges of immediate adaptability.
   The group discussed the limitations of current technologies, including AI, particularly in calculating wind conditions rapidly enough for real-time decision-making. In our solution the AI model is able to provide wind and turbulence in 5-10 s for the segment of city for a trip planned 2-3 days in advance. This should enable real-time. One speaker pointed out the need for dynamic notifications to inform all operators when structural changes occur in the airspace, emphasizing that contingency plans must be in place for unexpected scenarios.
   A broader discussion arose regarding the airspace structure itself. The speakers noted the potential for complications if unexpected numbers of drones entered a predefined airspace, illustrating the necessity for a flexible approach to accommodate sudden changes in traffic. Participants acknowledged the difficulties of presenting such dynamic systems and expressed a desire for innovative solutions to manage airspace efficiently under these conditions.

Finally, the conversation shifted towards identifying events that might trigger changes in the airspace, emphasizing the importance of quantifying these triggers to ensure effective responses to emergencies and other relevant situations.

- GPS-Denied Areas in Urban Environments as Constraint in Airspace Design.
  During the discussion, a participant raised the critical issue of GPS-denied areas in urban settings, emphasizing the importance of this constraint for drone operations. They noted that corridors could be beneficial because they allow for training vision-based systems for localization, enabling drones to navigate even in scenarios where GPS signals are weak or spoofed.
  The speaker highlighted the challenges they faced in navigating between tall buildings in urban areas, underlining the current difficulties in obtaining reliable GPS data in such environments. Another participant agreed, acknowledging that while this problem persists today, it may not be as significant in the future. However, it remains a crucial concern for the ongoing project.
  The conversation shifted to dead reckoning as a potential solution, with the speaker pointing out that many manufacturers employ this method in their Inertial Navigation Systems (INS). They explained that if drones can utilize dead reckoning effectively, they could maintain accurate localization for an extended period, even without GPS.

In summary, the complexities of planning airspace configurations for drone operations, focusing on aligning configurations with weather forecasts and other constraints are discussed. The approach involves setting airspace structures two to three days in advance, allowing planners to account for weather, environmental conditions, and anticipated noise impact. Historical drone traffic data, such as typical flight times and patterns, also could help to estimate expected traffic. While the system's adaptability ensures all potential drone movements are safely managed within set hours, creating a proactive and flexible framework for drone airspace design.

4. Session 2: Drone Flight Plan

Presenter: Emre Koyuncu from ITU.

4.1. Presentation

The second solution in the AI4HyDrop project is an autonomous flight plan approval service, as illustrated in Figure 7. This process includes two main components: U-Plan Authorization and U-Plan Recommendation. Once a U-Plan is submitted, the U-Plan Authorization system checks it for compliance with key criteria, such as weather conditions, demand and capacity balancing (DCB) for strategic planning, and conflict detection. If the U-Plan does not meet these requirements, the U-Plan Recommendation system will suggest updates that the drone operator needs to make for compliance. Once the U-Plan is approved, it moves to the flight activation phase in the pre-tactical stage, preparing it for the flight to commence.

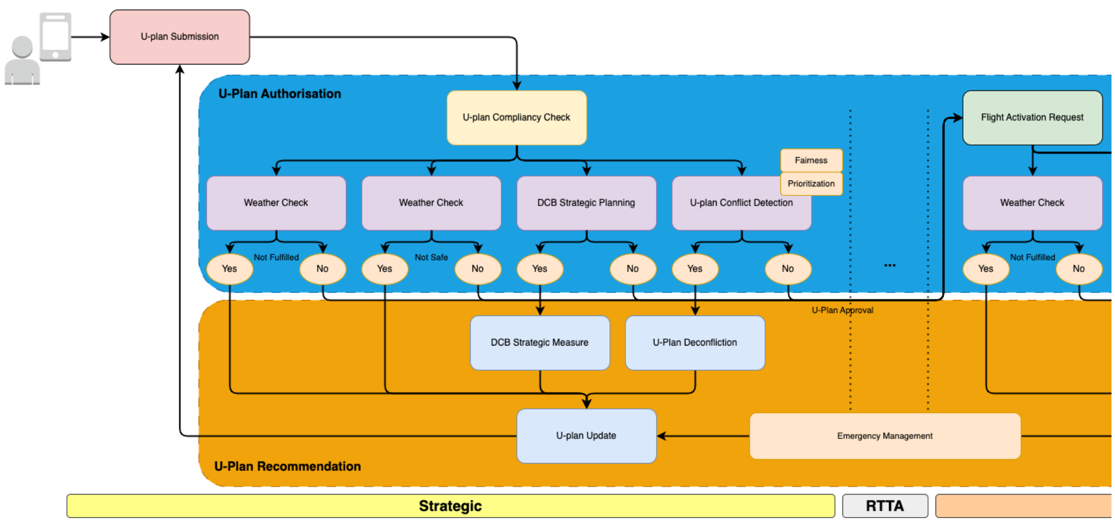


Figure 7: The flow of U-Plan approval process.

However, there are several issues in the drone flight plan approval process that need to be considered:

a. Increasing drone operations (various types, missions, models, etc.) are making it difficult to manually manage flight plan approvals.
b. Lack of efficient systems leads to delays in flight plan approvals, limits operational diversity and scalability.
c. Limited ability to assess real-time factors such as weather conditions, airspace restrictions, and traffic capacity for drones.
d. Current processes are resource-intensive and often involve manual intervention, resulting in inefficient use of airspace.

In current practice of drone flight plan approval process, the approach is:

a. Flight plans for drones are typically submitted manually, requiring air traffic controllers or aviation authorities to review each plan.
b. Existing systems are not fully integrated with real-time data, such as airspace usage and weather conditions, leading to potential conflicts or inefficient routing.
c. Drone operators rely on UTM (UAS Traffic Management) systems that are still in development or early stages of deployment – many concepts are not clear yet!

Despite the current process and condition of drone flight plan approval process, some developments are expected to be implemented in the future.

a. USSP (U-Space Service Providers) will play a central role, managing airspace and automating flight plan approvals for drones across various sectors.
b. CISP (Common Information Service Providers) will provide real-time data (e.g., weather, airspace capacity, traffic) to enable dynamic flight plan evaluations and approvals.
c. Prioritization mechanisms will organize airspace use, ensuring urgent or high-priority flights (e.g., medical drones) receive immediate approval.
d. AI-driven systems will fully automate flight plan approvals, ensuring safety, efficiency, and compliance with regulatory standards.
e. AI will not only facilitate decision-making but also support the generation of optimized U-Plans, tailored to meet the needs of operators while ensuring equitable and efficient use of the airspace.
f. Seamless integration between U-Space services and manned air traffic management systems to handle increasing drone operations safely and efficiently.

In AI4HyDrop project, an approach for drone flight plan approval process is proposed which consist of several steps:

- Step 1: U-Plan compliancy check. Different regions may have varying regulations and standards for Unmanned Aerial Vehicle (UAV) operations. Developing a standardized approach that can be adopted globally while ensuring compliance with local regulations is a significant challenge.
- Step 2: Strategic conflict detection. As the number of UAV operations increases (dreaming of cargo drones, medical drones, police drones, pizza delivery drones, and more), U-Space systems must be scalable to handle the growing volume of flight plans and ensure efficient management without compromising safety.
- Step 3: Seamless Integration with Dynamic Structure of Airspace. Automated systems rely heavily on accurate real-time data, including weather conditions, airspace restrictions, and the presence of other aircraft. The automated flight plan approval will connect to an extended CISP system to ensure the data is always current and reliable as shown in Figure 8. In this relation, an integration by Application Programing Interface (API) and Large Language Models (LLM) are used for the connection between the two systems.

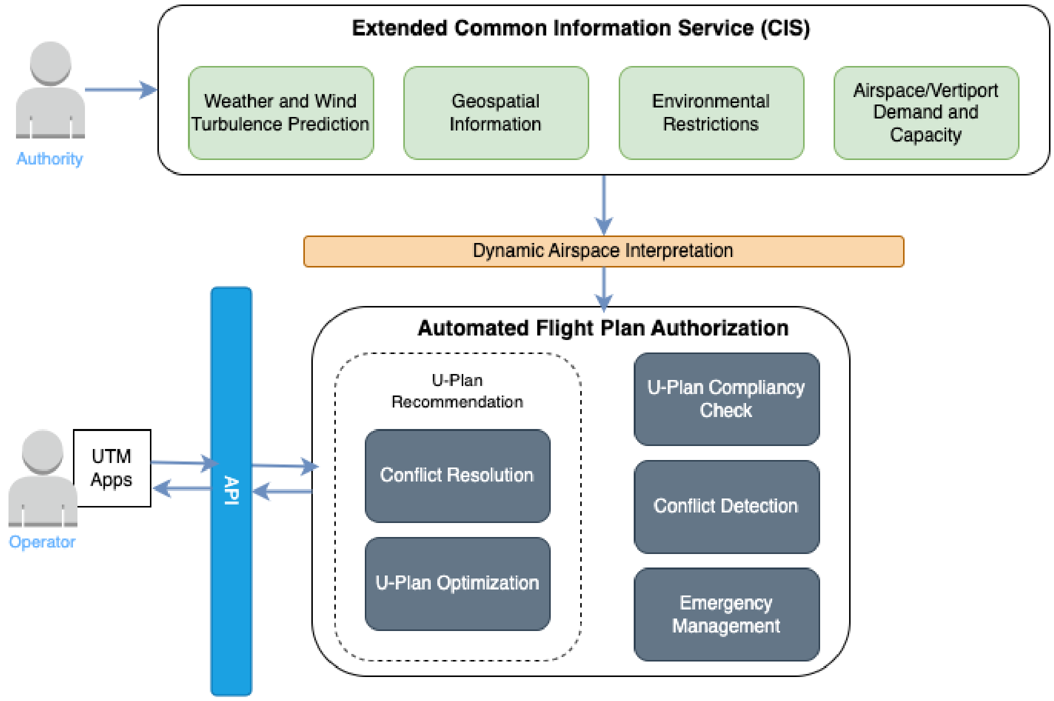


Figure 8: Connection of flight plan approval system and CISP.

- Step 4: Provide U-Plan Recommendation with AI. Developing equitable policies and systems to manage airspace access and flight approvals, ensuring that all users have fair access to the airspace, and some have priorities (police, medics, firefighters, etc.) when safety is concerned.
- Step 5: Validation. The concept of automated flight plan approval system will be validated using 2 use cases. The Duzce city use case is for emergency replanning case and the Prague city use case is for sudden weather change case. The validation has three objectives which are:
    - To access the compliancy of the received flight plans with the dynamic airspace structure in terms of geolocation, capacity, restrictions, weather and wind turbulence rate.
    - To assess the conflict of the received flight plans within reasonable time to act (RTTA) window according to their priorities and the uncertainty limits (type, performance, wind, etc.)
    - To provide recommendation actions to the operator of the rejected flight plan within RTTA window according to their rejection reason.

At the end of the presentation, several questions are asked to the participants for their answer as an input for further development of the solution. The questions are:

- Operational Feasibility:
    - "What do you think are the biggest challenges in fully automating flight plan approvals for both drones and manned aircraft? How could we overcome them?"

- Technology, AI and Safety:
  - "In your opinion, how reliable do you think AI systems are for making critical decisions in airspace management? How do we ensure that the AI models used for this purpose are unbiased and accurate?"
  - "With systems like Autonomous Flight Plan Approval Service (A-FPLAS) automating approvals, how do we ensure accountability for flight plan decisions in case of safety incidents or airspace conflicts?"
- Airspace Optimization:
  - "Considering the growth of drone traffic, what additional factors should AI-driven systems like A-FPLAS consider when optimizing flight plans and airspace usage?"
- Public Perception and Trust:
  - "What do you think the public's perception will be regarding AI systems managing airspace? How can we build trust in these technologies?"

4.2. Discussion

Several points were discussed during and after the presentation between the participants and the presenter. The main topics included:

a. The Role of AI and Automation in Decision-Making.
Participants explored the difference between AI and automation in streamlining complex decision-making processes. One key point raised was that automation can enhance efficiency by performing tasks similar to those of humans but at a faster rate, especially when processing large volumes of data. However, unlike humans, AI does not initiate actions independently but rather accelerates the execution of pre-determined tasks. Additionally, participants clarified that AI within automation systems often involves algorithms designed to mimic certain human cognitive functions, such as learning. This learning can occur both online (in real-time) and offline, allowing the system to evolve and improve its responses over time. The conversation highlighted a nuanced distinction between traditional automation, which typically relies on preset rules, and modern AI-driven systems, which utilize complex algorithms capable of learning and adapting within automated frameworks. This distinction suggests that AI adds a layer of adaptability and responsiveness to automation, though human oversight remains integral.

b. Optimizing Drone Flight Planning and Conflict Detection.
The discussion focused on how drone operators can submit their preferred flight paths and the role of dynamic flight planning systems in accommodating these preferences while managing airspace efficiently. Initially, an operator specifies waypoints (A, B, C, etc.) and flight preferences. This submission includes crucial data, such as aircraft type, performance capabilities, and operator credentials, allowing the system to understand each operator's requirements. This information enables conflict detection systems to dynamically adjust corridors and volumes based on demand and the physical characteristics of each drone. Additionally, participants noted that adapting these corridors in real-time is essential for

managing high-demand airspace, as it allows for a flexible allocation of space without compromising capacity. The discussion underscored the need for systems that not only handle straightforward route planning but also adjust based on airspace constraints and operator needs, enhancing both safety and efficiency in urban drone operations.

c. The Importance of Accurate Urban Models for Safe Drone Navigation.
Participants discussed the critical role of accurate city and building data in ensuring safe and reliable drone operations in urban areas. They highlighted the need for detailed, up-to-date urban models from CISP to help drones avoid collisions with buildings or restricted zones. This data is essential for creating flight paths that respect city infrastructure and accommodate existing urban constraints. Participants agreed that, while reliable data can enhance safety, uncertainties must be accounted for, as model accuracy may vary, especially in fast-evolving urban landscapes.

d. Regulatory Considerations for Drone Flights Over Urban Infrastructure.
The conversation also addressed regulatory constraints that impact drone navigation, particularly around flying over infrastructure like highways. Some regulations restrict drone flights over highways due to safety concerns, as a drone failure over these areas could result in significant accidents. However, in certain cases, flights over highways are considered to reduce noise disturbances in residential areas. This dual perspective creates regulatory challenges, as some routes must balance safety with noise mitigation goals. Participants noted that adherence to these regulations requires flexible, adaptable navigation systems that can balance safety, noise, and compliance with urban policies.

e. The Role of Human Oversight in AI-Driven Systems.
The discussion emphasized the importance of maintaining human oversight in AI-driven systems, particularly in high-stakes applications. Participants highlighted that placing complete trust in AI or automated systems is risky and that having a human operator involved in the approval process can provide an additional layer of safety. While technology may evolve over the next few decades, the current consensus supports a hybrid model where human intelligence complements AI capabilities to ensure decision quality and safety. This cautious approach allows AI to aid decision-making without the risk of unchecked automation.

f. The Need for Explainable AI to Build Trust.
Another key point was the necessity of explainable AI to foster trust in autonomous systems. Participants discussed research indicating that people tend to trust traditional autopilot systems more than AI-based systems, primarily because AI's decision-making process is often opaque. By making AI decisions more transparent and understandable, developers could increase user confidence and acceptance. Explainable AI would clarify how decisions are made, helping users understand why the system acts in certain ways, and making it easier to assess its reliability. This transparency is seen as vital for improving trust and ensuring AI is used responsibly across various applications.

g. Drone Flight Authorization and Activation.
To fly a drone, two main authorizations are required today based on SORA (Specific Operations Risk Assessment) with the process divided into a plan approval stage and a takeoff clearance stage. There is interest in fully automating at least the initial approval steps, with a two-step authorization aimed at increasing efficiency and maintaining safety standards. An analogy to early elevator systems, where people initially resisted automation, highlights the potential for future acceptance of automated systems in drone operations. Ideally, a combination of deterministic methods and machine learning could strengthen safety by balancing predictability and AI adaptability.

h. Drone Deconfliction and Uncertainty Management.
In the discussion, the group explores the challenges and strategies for managing drone deconfliction and trajectory uncertainties, emphasizing the need for both strategic and tactical approaches. A primary consideration is the role of police, emergency, and other transport systems in ensuring comprehensive detection and resolution of potential conflicts within the airspace. The discussion addresses the frequency and type of waypoints drones may follow (e.g., predefined routes like A-B-C-D), with speed and environmental factors, such as wind, contributing to uncertainty in drone trajectories. The reliability of communication and detection also plays a critical role; when detection is limited, uncertainty in the projected paths must increase to account for potential deviations.
The group debates the importance of "strategic deconfliction" to convince regulators that drones are kept safely separated in the airspace, potentially reducing the need for immediate tactical adjustments. They note, however, that strategic approaches could be enhanced by integrating tactical monitoring, enabling more flexibility in response to real-time conditions. This combined approach could allow strategic constraints to be relaxed, with tactical solutions offering backup where needed. By leveraging uncertainty management based on flow and the technical reliability of airspace monitoring, the discussion underscores how strategic and tactical coordination could help improve airspace safety in complex urban and restricted environments.

i. Leveraging AI and Machine Learning for Improved Airspace Management and Traffic Deconfliction.
The discussion highlights the importance of utilizing historical flight data to identify potential deviations and establish acceptable operational buffers. By deriving tables from this data, participants suggest that deterministic approaches can complement machine learning, enabling more effective traffic management strategies.
One approach shared involves managing compression on final approach of manned flight, where machine learning is employed to analyze real flight data and inform decisions on maintaining optimal aircraft speeds. Participants recognize the challenges posed by varying mission types and the complexities in calculating airspace volumes. The conversation emphasizes the need for algorithms that can adaptively manage these volumes based on mission parameters while acknowledging the limitations of traditional hand calculations.

A key point raised is the necessity of developing generalized models, particularly as air traffic scales up and flight patterns become less predictable. The dialogue underscores AI's strength in generalization, allowing for the creation of flexible and adaptable systems that can respond to the unknown variables inherent in airspace operations. This integration of AI with historical data not only enhances safety and efficiency but also facilitates a more dynamic approach to managing the increasingly complex air traffic landscape.

In summary, drone flight planning was emphasized for its reliance on operator preferences and the need for real-time corridor adjustments. Accurate urban models and regulatory compliance, especially concerning infrastructure overflights, are essential for safe operations. Human oversight remains crucial in high-stakes AI applications, and explainable AI is needed to build trust in automated systems. Authorization processes, deconfliction methods, and the potential of AI to enhance airspace management were also central topics, underscoring the balance between automation and human control.

5. Session 3: Drone Detection and Communication

Presenter: Enrique Puertas and Geronimo from UEM for drone detection, and Neno Ruseno from USN for communication section.

5.1. Presentation

The third solution in the AI4HyDrop project is the drone detection and communication. The main objective is to detect drones flying over restricted areas and establish effective communication with the operator to correct the situation. Restricted areas in urban environments can be airports, stadiums, military facilities, government buildings, etc. While the technology used to detect drones in airports and military environments may not be the most suitable for cities (cost, regulations, etc.). In this project, the detection process includes an AI-based drone detection system, checking the drone flight plan to confirm the access to the restricted area, and establishing the communication service to the drone operator to inform the necessary actions to be taken.

To detect a drone, there are 5 methods commonly employed:

a. **Computer Vision-based Approaches**: This technique utilizes cameras or sensors to capture images or videos and apply computer vision algorithms to detect drones based on their visual features such as shape, size, color, and motion patterns. Techniques such as object detection, image segmentation, and tracking can be employed. The most common solutions to image processing using approaches, such as Convolutional Neural Networks (CNNs), specifically YOLO (You Only Look Once) [14], [15], [16].

b. **Acoustic Detection**: Drones emit distinct sounds, which can be captured by microphones and analyzed using machine learning algorithms. Audio-based detection can involve techniques like spectrogram analysis, signal processing, and pattern recognition to distinguish drone noise from background noise. Machine learning models such as Support Vector Machines (SVMs) [17] or Recurrent Neural Networks (RNNs) [18] can be applied in this context.

c. **Radar Signal Analysis**: Radar sensors can detect drones based on their electromagnetic signatures. Machine learning algorithms can analyze radar signals to identify drones by recognizing their unique signatures or behavioral patterns [19]. Classification algorithms like Random Forests, Gradient Boosting Machines, or Deep Learning models can be used for this purpose.

d. **Radio Frequency (RF) Signal Analysis**: We can use classic classification techniques such as Random Forests or Deep Learning models to detect drones based on RF signals [20]. The algorithms will work by analyzing the radio frequency signals emitted by the drones to identify their presence. When the algorithm learns the drone's RF signature, it will be able to differentiate it from other noise sources.

e. **Sensor Data Fusion**: Combining information from multiple sensors, such as cameras, microphones, and radars, can enhance drone detection accuracy. Machine learning techniques such as ensemble learning, or multi-modal fusion algorithms can integrate data from different sources to improve detection reliability and reduce false positives [21], [22].

In drone detection, various sensors provide unique advantages and limitations, affecting their suitability for different scenarios. Below is an extended explanation of the pros and cons associated with each type of sensor:

a. RADAR
- Pros: RADAR sensors, particularly those specialized for small object detection, offer high precision in identifying drones, which is crucial for situations that demand accuracy, such as urban or restricted airspaces. Their ability to detect small objects ensures better reliability in complex environments, where drones may be difficult to distinguish from other objects.
- Cons: The primary drawback of RADAR sensors is their cost, which tends to be high, especially for specialized models. This can make large-scale deployment costly and may limit their use to high-priority areas where budget constraints are less of a concern.

b. Optical (Image/Video)
- Pros: Optical sensors, which use image or video capture, offer medium to high precision at a more affordable cost compared to RADAR. They provide the benefit of visual confirmation, allowing operators to assess drone characteristics, type, and behavior. Optical sensors are effective over a reasonable range, which makes them versatile in various settings.
- Cons: However, optical sensors can be limited by environmental factors, such as lighting and weather conditions, which can degrade their accuracy. Their performance may also be affected by the distance of the drone from the sensor, potentially reducing effectiveness for long-range detection.

c. Audio
- Pros: Audio sensors offer a highly affordable solution for drone detection. They are low-cost and can cover broad areas by detecting sound patterns that indicate the presence of drones, making them a feasible option for environments where budget and simplicity are prioritized.
- Cons: A significant drawback of audio sensors is their poor precision, as background noise and other sound interference can lead to inaccurate detections. This makes audio-based detection less reliable, especially in environments where accurate identification is necessary.

d. Radio Frequency (RF)
- Pros: RF sensors can detect signals from drones that use radio frequencies to communicate with operators, providing a valuable detection method for actively

controlled drones. They are particularly useful in identifying and tracking drones based on RF signature.
- Cons: However, RF sensors are ineffective for detecting unmanned drones that operate autonomously without RF signals. Additionally, regulatory issues surrounding RF detection and potential privacy concerns can restrict their use in certain areas or applications. This can complicate deployment, particularly in regulated or densely populated zones.

However, in the project, RADAR is not being considered for drone detection due to several factors:

- Availability of Commercial Solutions: There are already radar-based detection systems in place, particularly in critical areas such as military operations and airport security. These sectors benefit from the high accuracy and specialized functionality of RADAR, which suits the high stakes demand of these environments. However, since these commercial systems are well-established in such sectors, their inclusion in the current project may be redundant, especially where different priorities exist.
- High Cost: The cost of radar-based solutions is significant, typically ranging from 25,000€ to 200,000€. This makes RADAR systems prohibitively expensive for non-critical or smaller-scale applications, such as those involving local or urban areas that do not have extensive budgets.
- Affordability for Small Cities: Smaller cities and municipalities, which often operate on limited budgets, would find it difficult to justify the cost of RADAR solutions. These cities may have other essential expenses that take priority over high-cost RADAR systems, making it challenging to allocate resources to a technology that is more suitable for larger, well-funded organizations.

The drone detection solution leverages image-based detection using the algorithm as shown in Figure 9. The YOLO is a real-time object detection algorithm that identifies objects in images or video frames. Unlike traditional methods that scan an image in sections, YOLO processes the entire image at once, making it faster and more efficient. It divides the image into a grid and predicts bounding boxes and class probabilities for each section, allowing it to quickly locate and classify objects with high accuracy. This speed and accuracy make YOLO especially suitable for applications requiring real-time detection, like drone detection systems.

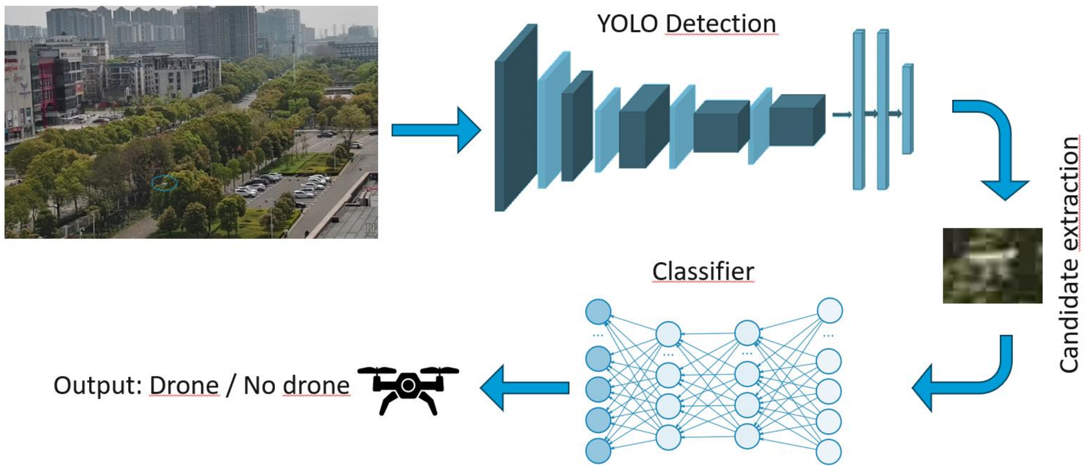
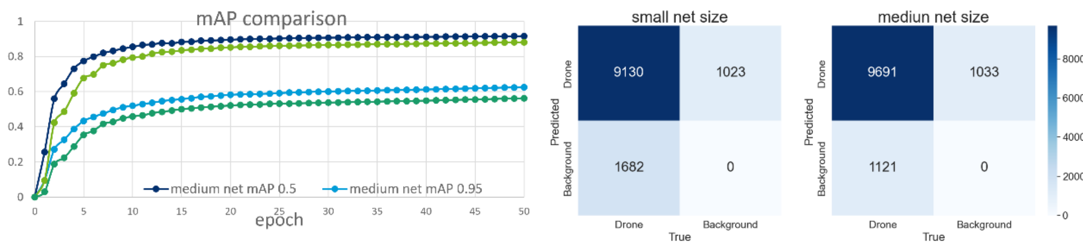


Figure 9: YOLO algorithm for drone detection system.

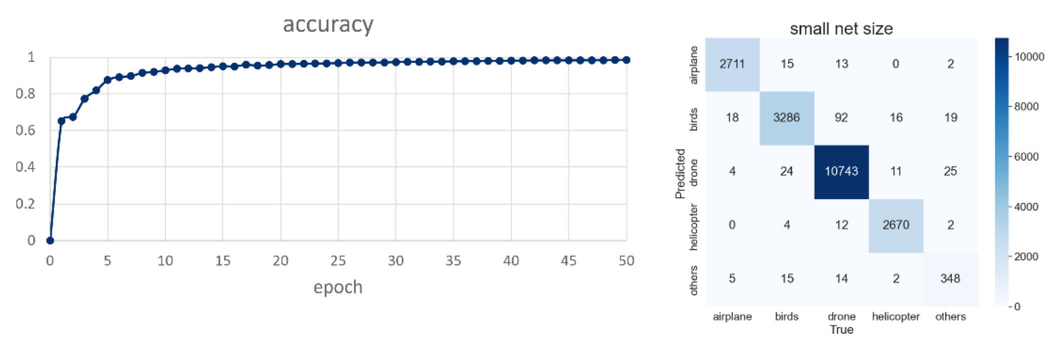
We trained the system with a dataset comprising 20,000 images, covering a variety of flight scenarios and conditions to enhance its robustness and accuracy in diverse environments.

- Multiple Flight Scenarios: The dataset includes images from different environments to ensure effective detection across various scenarios:
  - City: Urban landscapes with potential background clutter from buildings, people, and vehicles.
  - Beach: Open areas with natural features, possibly including dynamic elements like moving water and people.
  - Rural: Landscapes that may include vegetation, open fields, and fewer artificial structures.
- Different Flight Conditions: To further enhance detection accuracy, the dataset includes images of drones under various conditions:
  - Close Flight with Clear View of the Drone: These images provide clear details of the drone, aiding in precise detection when the drone is near the camera.
  - Distant Flight with Complex View of the Drone: These images simulate conditions where the drone is farther away, possibly blending into complex backgrounds, which makes detection more challenging.

By training on this diverse dataset, the YOLO algorithm is better equipped to detect drones in different scenarios and conditions, making the solution adaptable to real-world applications. The resulted model is evaluated in the accuracy to detect drone and classify the object (drone/no drone) as shown in Figure 10.



(a)



(b)

Figure 10: Result of YOLO: (a) drone detection and (b) drone classification.

The result shows the precision and efficiency of a real-time image processing system, which achieves an impressive accuracy rate of 92 to 96%. This system is capable of processing up to 60 images per second using a standard laptop. The results are presented through a confusion matrix, illustrating the predictions against the actual ground truth, highlighting the system's ability to distinguish between real and drone images effectively. Two models are employed: a smaller model for less powerful hardware and a medium model for more robust systems. This flexibility allows the system to adapt to varying hardware capabilities across different urban areas, ensuring optimal performance even in resource-constrained environments. While the smaller model may not achieve the same high precision as the medium model, it is designed to function effectively on devices with limited processing power, ensuring accessibility and efficiency in diverse settings.

In the latest research development, audio recognition is solved as an image analysis problem and flow process is shown in Figure 11. The process involves converting audio signals into spectrograms, which are graphical representations of the audio data. This transformation allows for the utilization of the same classification technologies used in image analysis. The objective is to classify various sounds captured by microphones, determining whether the detected noise is isolated or part of a more complex audio environment. By leveraging these advanced techniques, the system aims to enhance its ability to interpret and analyze audio inputs effectively.

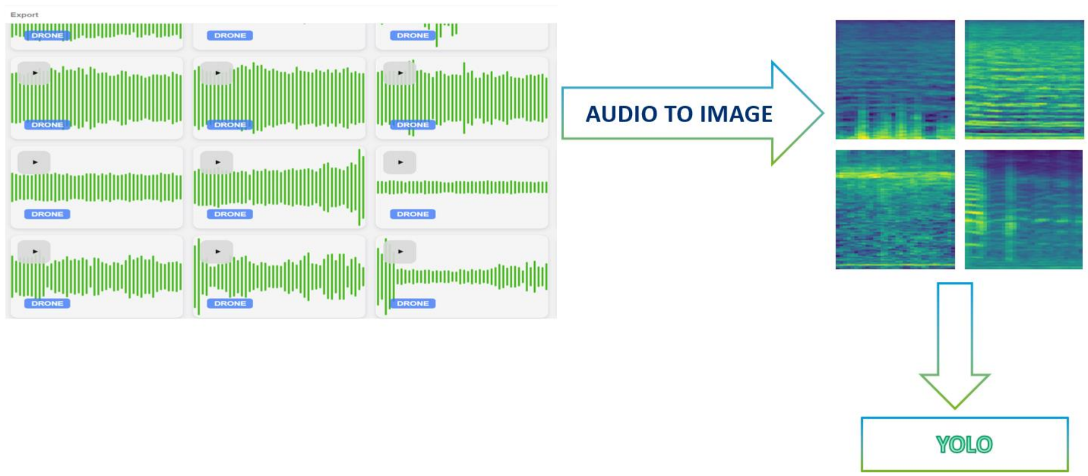


Figure 11: The process of audio detection of drone.

In this project, a fusion model of AI using several sensors is proposed to improve the accuracy and reliability of the system as shown in Figure 12. It addresses the development of specialized machine learning models for different sensors, specifically audio and images. Currently, the team has created distinct models for these two modalities and is in the process of building additional models for radio frequency and radar data. The goal is to integrate these various models using a committee decision-making approach, which will weigh the contributions of each sensor according to their accuracy. For instance, while the audio classifier may have lower accuracy, its influence on the final decision will be less significant compared to the image classifier, which boasts a precision of 90 to 95 percent. This weighted approach aims to enhance the overall reliability and effectiveness of the classification system.

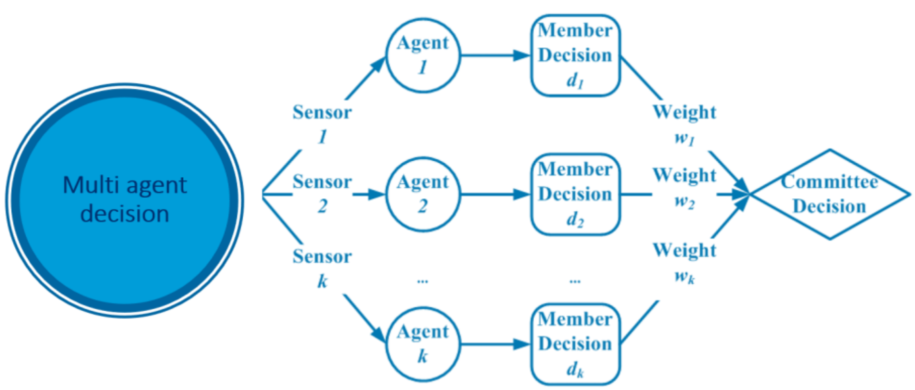


Figure 12: The fusion model of AI for drone detection.

The other issue is about the feasibility of building a drone detection system using AI without the need for extensive training data or specific models. With the rapid advancements in AI, particularly with the emergence of generative AI, it is important to explore how these new models can be leveraged for drone detection.

In recent years, advancements in AI have led to the development of large language models that initially focused solely on text processing. These models were capable of answering basic questions, summarizing content, and translating text. However, as technology has progressed, these models have evolved into multimodal systems that can process various types of data, including images, audio, and video. For instance, when given an image of a cat, the model can accurately identify the cat while indicating the absence of a UAV (unmanned aerial vehicle) in the image. This evolution reflects the models' training on millions of images, allowing them to understand a wide range of objects beyond the specific data they were initially trained on.

Recognizing this potential, researchers considered whether multimodal models could assist in drone detection. Unlike traditional models that required extensive datasets—such as the 20,000 images used in previous studies—they aimed to achieve satisfactory results with around 400 images containing drones, each annotated with a bounding box to indicate the drone's location. These images were categorized into two types: those where the drone was the focal point and others where it blended more into the background. The latter poses significant challenges, particularly at night when drones can camouflage effectively. After collecting and processing the images, the team needed to select an appropriate model for inference that aligned with their project goals. With numerous commercial solutions available, including ChatGPT and Google's Gemini models, the next steps involve evaluating the model's performance in detecting drones within the context of their research.

The team chose a model known as "Gwen," which is part of a family of visual language models developed by Alibaba Cloud in China over the past four to five years. They opted for the open-source version of this model, which contains seven billion parameters. While not the smallest model available, it strikes a balance between size and performance, making it fast and cost-effective to run. This model can efficiently operate on a GPU with 16 gigabytes of RAM, which is relatively inexpensive to acquire.

In collaboration with top engineers, the team created prompts for image analysis and began evaluating the results. They utilized high-performance hardware, specifically an L4 model optimized for AI, equipped with 64 gigabytes of RAM. Given the dense nature of these models, they require significant storage—around 20 to 25 gigabytes—and take approximately 75 seconds to load. Once operational, the inference time for processing images averaged about 1.16 seconds each, making the model quite efficient.

When testing the model with the initial set of 400 images, they achieved an impressive detection rate of 81.5% for images containing drones, while the model correctly identified 85.5% of images without drones. This level of accuracy is particularly notable given the challenges associated with detecting small objects in complex backgrounds, demonstrating the model's effectiveness in real-world scenarios.

It is crucial to evaluate whether the model accurately understands what constitutes a drone, as there is a risk of it "hallucinating" detections—essentially, identifying non-existent drones. To assess this, the team employed a method known as Intersection over Union (IoU) as shown in Figure 13. This technique involves comparing the original bounding box, which indicates the true location of the drone, with the bounding box predicted by the model. For instance, if the original bounding box is represented by a red rectangle and the model predicts a green rectangle, a lack of overlap indicates an incorrect detection.

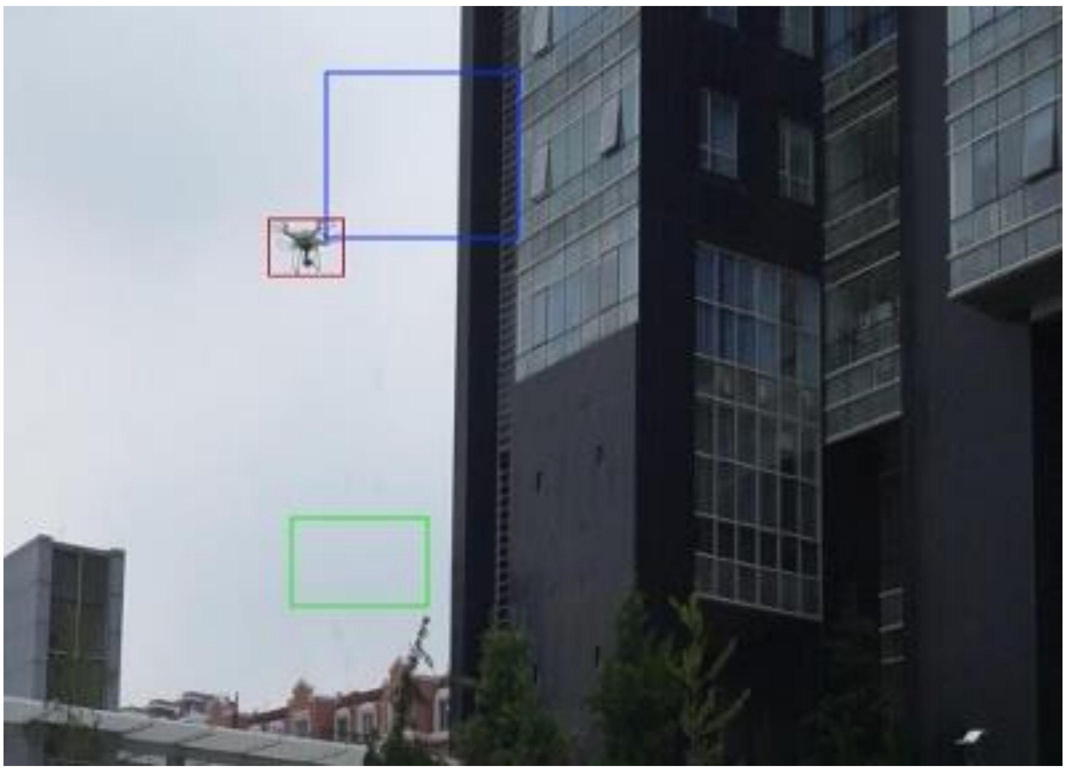


Figure 13: Intersection over Union (IoU) method.

The team established a threshold for determining successful detections, deciding that an overlap of more than 50% between the bounding boxes would qualify as a good detection. Initial results were surprising; while the 0.5 threshold is standard in academic settings, they found that this led to a precision rate of only about 23%, which is disappointing as shown in Figure 14. Recognizing the challenges of detecting small objects, they explored a lower threshold of 0.3, which yielded a precision of 50%. This suggests that while the model may have a general understanding of what a drone is, it struggles to pinpoint their exact locations accurately, indicating a need for further refinement in the model's detection capabilities.

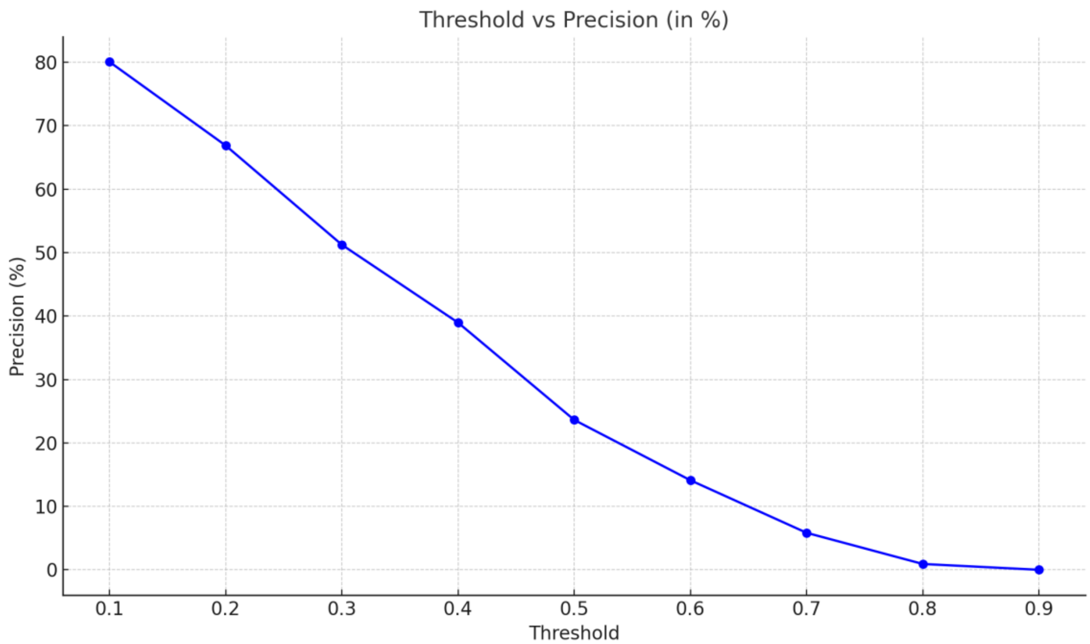


Figure 14: Intersection over Union (IoU) method.

The primary goal of this exercise was to ascertain whether the model could effectively detect drones within specified coordinates. The results indicated that the model accurately identifies the presence of a drone in the image approximately 82% of the time. However, when it comes to localizing the drone's exact position, the model's performance significantly declines, leading to uncertainty about its detection capabilities. This discrepancy raises concerns about potential false positives, where the model might simply be "hallucinating" detections without actually confirming their validity.

Despite these challenges, there is a consensus that technology continues to improve year by year, and with advancements in AI models, the detection thresholds are likely to rise over time. It is also important to note that the current detection process is not real-time, which poses a limitation for practical applications. Nevertheless, the emergence of new AI architectures holds promise for enhancing processing capabilities in the future.

The overall framework for drone detection and communication is shown in Figure 15. It considers both cooperative drones that transmit their positions via broadcast or network Remote ID and non-cooperative drones that do not broadcast their positions and identification. There are three case studies of drone detection identified in this research that consists of:

1. Cooperative drone that is authorized to fly into restricted airspace:
    - A drone is detected by sensors flying near a restricted airspace and its location is estimated.

- The broadcast Remote ID data is received including its ID and location.
- The detection system connects to the Extended CISP to get the flight plan authorization data.
- The data received confirms that the drone is authorized to fly in restricted airspace and the case is closed.

2. Cooperative drone that is not authorized to fly into restricted airspace:
   - The drone is detected by sensors flying near a restricted airspace and its location is estimated.
   - The broadcast Remote ID data is received including its ID and location.
   - The detection system connects to the Extended CISP to get the flight plan authorization data.
   - The data received confirms that the drone is not authorized to fly to the restricted airspace
   - A warning level 1 (including drone ID and its location) is sent to the USSP to notify the operator to stay away from the restricted airspace.
   - The drone operator commands the drone to return to its planned trajectory and the case is closed.
   - If the drone continues to be nearer to the restricted airspace, it becomes a non-cooperative drone (case number 3).
3. Non-cooperative drone that flies into restricted airspace:
   - A drone is detected by sensors flying near a restricted airspace and its location is estimated.
   - No broadcast Remote ID data is received or the non-cooperative drone case from case 2.
   - A warning level 2 (including drone location) is sent to the USSP to notify all the operators in the area, trigger any tactical deconfliction measure and warn the security personnel to take the necessary actions.

The mechanism of transferring warning information to the USSP has a significant role in the drone detection framework because the information should be transferred as quickly as possible to the related parties to take necessary action to avoid a further catastrophic event. In this research, it is assumed that the detection system and USSP are connected by internet communication that is available in most countries using API to exchange the information such as warning from drone detection system. An API describes how users (also called clients) requests information of actions to a server. These requests usually need to determine the values of some parameters, for instance, the date when booking a flight or username and password.

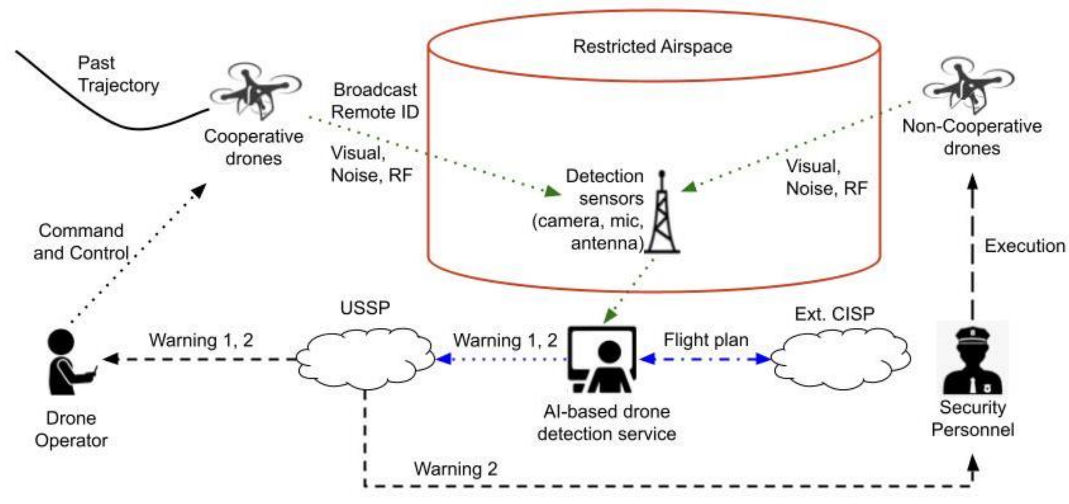


Figure 15: Framework of drone detection and communication.

The proposed warning message submitted through the API is in the form of JavaScript Object Notation (JSON) format as shown in Figure 16. JSON is a widely used format to gather and send the pairs of names of parameters and its values in a readable way. In our case, the warning message sent from the drone detection system to the USSP server contains the parameters timestamp, representing the moment the drone was detected; warning, to identify the type of warning; droneID, when it was possible to identify the drone, this value represent its plate or unique identifier; warning level, it is used to determine the severity of the situation used for instance to determine how to display the warning in the pilot interface; longitude, latitude, and relative altitude which represent the detected drone position; reason to explain more detail on the warning situation; and token that represent the security key to access the USSP system.


```
{
    "droneId": "123456789ABCDE",
    "timestamp": "2021-04-27T16:48:05+02:00",
    "warning": "drone_detection",
    "warning_level": 1,
    "lon": -7.460771,
    "lat":  43.113822,
    "alt_rel": 50.0,
    "reason": "Violation of NFZ X. Exit the area immediately.",
    "token": "eyJhbGciJIUzI1...AzFUD7SvMmSA"
}
```


Figure 16: JSON format of the warning message.

To evaluate the communication system for drone detection, the sender of information is from an office computer using Windows OS running a Python script in the University of South-Eastern Norway in Kongsberg campus and the receiver of information is the DLR

U-Space Research Environment (DURE), hosted in Amazon Web Service (AWS) cloud servers located in Frankfurt, Germany, running on an Amazon Linux server instance. In the experiment of initial validation process, the latency and throughput are calculated for the combination of message intervals (1000ms, 500ms, 100ms, and 10ms), and message payload size by varying the reason text (small (62 bytes), medium (234 bytes), and large (1,844 bytes)). The message intervals and sizes are selected to represent the most possible settings in the drone operations without trying to get the limit of server capability. The system sends 100 messages for each case to avoid the experiment to be considered as (DDoS) attack. Furthermore, there could be multiple drone detection systems that operated in a U-Space airspace. To simulate this condition, an experiment with two computers sending messages at the same time (twin system) is conducted to evaluate the communication performance. The experiment for single system is conducted twice before and after the experiment of twin system.

Latency statistics for selected intervals and payload sizes are illustrated in Figure 17 with the red diamond indicates the mean value and the black line in the middle of boxplot indicates the median value. The results indicate similar latency values for intervals of 100 ms, 500 ms, and 1000 ms. However, a significant increase in latency is observed at a 10 ms interval, suggesting that this interval is approaching the limit of the USSP system's capability to receive warning messages, as system performance begins to degrade.

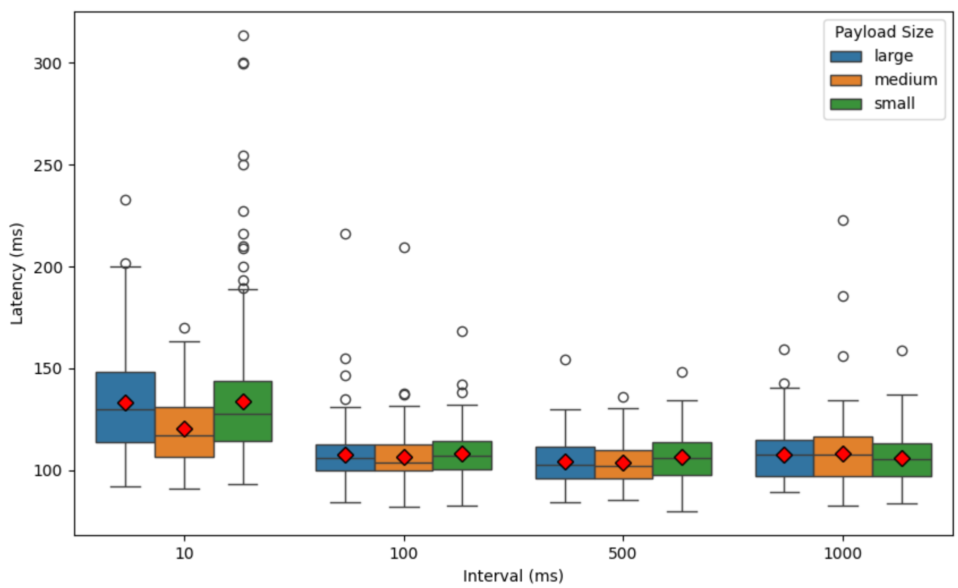


Figure 17: Latency result of communication of drone detection.

At the end of the presentation, a question is asked to the participants with regards to which ground communication protocol will be used in the U-Space operation?

5.2. Discussion

Several points were discussed during and after the presentation between the participants and the presenter. The main topics included:

a. Using Neural Network (NN) algorithms for Drone Detection.
The discussion focuses on the integration of neural networks (NN) for improving model explainability in classification tasks. One participant suggests the possibility of utilizing another neural network to enhance the output interpretation of the final classification. The current model operates somewhat like a "black box," making it challenging to understand the reasoning behind its classifications. By integrating another NN, the team could provide clearer explanations of the model's decisions, including probabilities for different classifications. However, this approach poses significant challenges, as developing such models is complex, computationally demanding, and requires high-quality data. The speaker also notes that the existing model does not function well in certain conditions, emphasizing the need for a robust dataset to ensure effectiveness.

b. Dataset Training and Detection Capabilities.
During the discussion, the participants explored the assessment process involving the evaluation of 400 images for drone detection. While the model in question, from the Gwen family, had already been trained, it was clarified that no separate validation phase was necessary. Instead, the entire dataset could be utilized directly to assess the model's accuracy. The results indicated an 81.5% detection rate, with approximately 330 images confirming the presence of a drone, while around 70 images failed to detect drones that were indeed present.
The conversation highlighted the challenges faced when the drones were photographed at night. It was noted that many of the undetected instances were due to the lack of lighting on the drones, which made them harder to identify. In contrast, drones equipped with LED lights were easier for the model to detect, especially in low-light conditions. This pointed to the need for further refinement in detection capabilities, particularly for scenarios involving unlit drones at night, which remain a significant obstacle in achieving higher accuracy.

c. The Potential of Multi-Model Approaches and Video Analysis in Drone Detection.
The discussion raised two key questions regarding the improvement of drone detection systems. First, the idea of combining different models to enhance detection accuracy was proposed. This approach, often referred to as "multi-voting," involves utilizing several models simultaneously and determining a consensus based on their outputs. For instance, if ten models are employed and seven indicate the presence of a drone while three do not, the majority vote could serve as a reliable indicator of detection. This concept aligns with the need for a more robust system that integrates various inputs, similar to how sensor fusion works in other applications.

The second question focused on the limitations of static image analysis for drone detection. It was noted that images alone might not provide a definitive answer, especially when considering factors like camouflage and the movement of drones. Instead of relying solely on still images, it is suggested that a more effective approach would involve analyzing video footage. By observing the movement patterns over time, a system could make more informed assessments. Advances in models, such as Google's Gemini, allow for the processing of longer video clips, enhancing the capability to track drones as they move across different frames. This shift toward video analysis represents a promising direction for future drone detection systems, improving both accuracy and reliability.

d. Consistency of AI Responses in Drone Detection.
A question arose regarding the consistency of responses from an AI model when presented with the same image multiple times. Specifically, if the same image were fed to the model ten times, would it yield the same output each time? While there hasn't been extensive testing to confirm this, it is suggested that the model might produce varying responses—potentially resulting in a 50/50 split between consistent detections and those influenced by the model's tendency to hallucinate. This unpredictability underscores the complexities involved in AI detection systems, particularly when images are not distinctly defined. Further experimentation is needed to assess the reliability of responses and understand how often the model's outputs may change with repeated inputs, which could significantly impact the overall performance and trustworthiness of the drone detection system.

e. The Role of Feedback Quality in AI Detection Reliability.
The reliability of AI detection systems, such as those used for drone identification, hinges significantly on the quality of input data and the feedback provided during the detection process. When the model encounters weak feedback, it may yield random results or percentages, leading to inconsistent outputs. Conversely, strong feedback can enhance the model's determinism, allowing it to return consistent results in similar conditions. It's important to note that the visual context in which the images are captured can further complicate detection; for instance, images taken in uniform backgrounds, like a clear blue sky, may make it easier to identify a drone compared to those cluttered with other objects, such as trees or buildings. This complexity underscores the need for a refined approach to probability weighting in multi-model systems. By adjusting the weight assigned to detections based on the strength of feedback—lowering the weight for low-probability detections—one can potentially enhance overall accuracy. Additionally, the discussion highlighted ongoing efforts to incorporate noise and other variables into the detection framework, indicating a commitment to improving the robustness and precision of AI-driven detection models in various scenarios.

f. Assessing Latency in Drone Detection Communication Systems.
The team is currently studying the latency in communication systems for drone detection, with a particular focus on the time required for information to be

transmitted from detection to the operator. While there isn't a definitive time frame yet, tests are ongoing to understand how efficiently these systems perform. Initial studies involve connecting the detection system with the USSP to measure the communication delay between detection and receipt. These preliminary results will provide insights into optimizing real-time responsiveness in drone monitoring operations.

g. Communication Challenges in U-Space for Cooperative and Non-Cooperative Drones.
   In U-Space airspace, there's an ongoing exchange between drone operators and the USSP, which streamlines communication and monitoring of cooperative drones. When operating within designated U-Space, authorized drone paths are tracked, so deviations are quickly detected as part of routine conformance monitoring. This continuous communication channel simplifies responses to anomalies since any deviation from the authorized path is identifiable. However, the challenge arises with non-cooperative drones—those that may unexpectedly appear in restricted areas without prior communication or authorization. To manage these cases, protocols are being developed to include sudden detection measures, ensuring that non-cooperative drones can be identified and managed swiftly to maintain airspace safety.
h. Communication and Monitoring Protocols for Drone Operations in U-Space.
   Effective communication between drone operators and USSPs is essential for managing both cooperative and non-cooperative drones in U-Space. To improve these interactions, stakeholders are exploring partnerships with teams experienced in prototyping multi-USSP systems, which enhance collaboration across different providers. These systems require a robust interface for communication between the drone operator and USSP, typically through protocols like System Wide Information Management (SWIM) to facilitate seamless data exchange.
i. Detection Protocols for Unauthorized Drones in U-Space.
   A layered approach is essential for managing unauthorized or non-cooperative drones in U-Space and restricted airspaces. Traditional airspace monitoring relies on primary radar systems to identify every aircraft, particularly non-cooperative ones that lack active transponders. To streamline these responses, communication pathways are often set, such as routing information through CISP before reaching police forces. This structure ensures accurate and regulated decision-making when responding to unauthorized aircraft in restricted airspace.
j. Challenges in Contacting Drones Operator in U-Space.
   In the context of U-Space operations, Remote ID is crucial for identifying and locating drone operators. However, several challenges impact its reliability, primarily due to latency issues and difficulties in real-time operator contact. Although Remote ID is designed to broadcast the operator's or remote pilot's position, contacting them in real-time can be unpredictable. Despite regulations stipulating that operator contact details should be included, such as a phone number, there is inconsistency in

reaching operators promptly. Trials have shown that issues like device battery depletion and connectivity challenges hinder the effectiveness of Remote ID in certain areas.

The discussion highlights various aspects of AI-driven drone detection and monitoring within U-Space, covering both technical and operational challenges. Multi-model approaches and video analysis were suggested to enhance detection accuracy, especially under challenging conditions like nighttime or when dealing with unlit drones. Communication protocols and latency concerns are critical in U-Space, where maintaining real-time data exchange with both cooperative and non-cooperative drones is essential.

6. Summary

The 2nd workshop of AI4HyDrop was successfully conducted to present the progress of the project to the expert advisory boards and SJU officers, and to gather some feedback and inputs for the development of the solutions. The key points from the discussion are:

Session 1: Airspace Structure

- Advance Planning: Airspace configurations are set two to three days before operations, using reliable weather forecasts to align structures with expected conditions and constraints.
- Historical Traffic Data: Planners use historical data, such as recurring patterns in drone traffic (e.g., during school commutes), to estimate drone activity and prepare the airspace accordingly.
- Environmental and Noise Considerations: Environmental and noise constraints are factored into the planning process to minimize impact on urban areas.
- Safety and Efficiency Focus: Proactive and adaptable airspace planning ensures safe and efficient drone operations by balancing predictive and real-time data to meet urban airspace demands.

Session 2: Drone Flight Plan

- Drone Flight Planning: Operators submit preferred routes and relevant data, which the system uses to detect conflicts and adjust airspace corridors dynamically.
- Urban Models for Safe Navigation: Accurate city and building data are essential for collision avoidance and respecting urban constraints, though uncertainties in models require caution.
- Regulatory Constraints: Regulations limit drone operations over infrastructure, like highways, balancing safety and noise considerations; flexible systems help meet these regulations.
- Human Oversight in AI Systems: Human involvement in AI-driven systems remains essential to enhance safety and decision-making quality in critical scenarios.
- Drone Authorization: Two-stage authorization (plan approval and take-off clearance) is key to safety; automation can streamline initial steps, increasing acceptance of these systems.

Session 3: Drone Detection and Communication

- Dataset Training and Detection Accuracy: Evaluating the model's 81.5% detection rate highlighted the challenges of detecting drones in low-light conditions, with LED-equipped drones more easily identified.

- Multi-Model and Video-Based Detection: Multi-model approaches and video analysis, rather than static images, are more effective for drone detection, especially in tracking drones across frames to improve reliability.
- Consistency in AI Outputs: The reliability of AI models in drone detection can vary, with potential inconsistencies in output for repeated images, indicating a need for further testing to improve consistency.
- Impact of Feedback Quality: Strong, quality feedback in detection improves the model's accuracy, while weak feedback increases inconsistency, emphasizing the importance of high-quality inputs.
- Latency in Communication: Testing latency between detection systems and operators is essential to ensure responsive, real-time communication in drone monitoring operations.
- U-Space Communication for Cooperative vs. Non-Cooperative Drones: Effective communication protocols allow for easy monitoring of cooperative drones, while new detection protocols for non-cooperative drones helps maintain airspace safety.
- Multi-USSP Collaboration in U-Space: Stakeholders are enhancing communication through multi-USSP systems, leveraging protocols like SWIM for seamless data exchange among service providers.

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This Project has received funding from the SESAR3 Joint Undertaking under grant agreement No. 101114805 under European Union's Horizon Europe research and innovation programme.