Technische Hochschule Ingolstadt

Faculty of Computer Science

The Future of AI in Air Traffic Management: Coordinating Autonomous Airliners and UAM within Busy Airspaces using AI

Seminar Paper

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Date: 29 May 2025

Affidavit

I certify that I have completed the work without outside help and without using sources other than those specified and that the work has not yet been submitted in the same or a similar form to any other examination authority and has been accepted by them as part of an examination. All statements that have been adopted literally or analogously are marked as such.

Ingolstadt, 29 May 2025

Signature

Acronyms

AG Attention Guidance. 9
AI Artificial Intelligence. 1–3, 5, 7–9
ATC air traffic control. 8
ATCO air traffic controller. 1–3, 8, 9
ATM Air Traffic Management. 1–5, 8

BATMAN Boundary Arrival Task Manager. 9
Bi-LSTM bidirectional long-short term memory. 7

CoDiST Controller Display and Simulation Tool. 8
CTU Chengdu Shuangliu International Airport. 2
CWP controller working position. 8, 9

DAS Dynamic Airspace Sectorisation. 6, 7
DASIM Data And Service Integration Module. 8
DBSCAN Density-Based Spatial Clustering of Applications with Noise. 7
DHM Dynamic HeatMap. 9
DIRC Digital Interactive Radar Controller. 8

EA evolutionary algorithm. 6, 7
eVTOL electric vertical takeoff and landing. 1

FMC Flight Minimum Cost. 2
FMS Flight Minimum Shift. 2

HAT Human-Autonomy Teaming. 8

IFR instrument flight rule. 2

LUM Dehong Mangshi International Airport. 2, 3

MTL multi-task learning. 7
MVP Modified Voltage Potential. 4, 5

TCC Trajectory Conflict Checker. 8
TCZ Tengchong Tuofeng Airport. 2, 3
TFT Temporal Fusion Transformer. 7
TraGAT Trajectory Generation and Advisory Tool. 8

UAM Urban Air Mobility. 1, 3

UAS unmanned aerial system. 1, 3

UAV unmanned aerial vehicle. 3, 5

UTM Unmanned Traffic Management. 1

Abstract

The summary gives the reader a rough overview of the content (brief problem definition, approach, solution approaches and possibly key findings). The scope should be about half a page. This chapter is not mandatory and should only be considered optional.

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1 Introduction

The rapid advancement of aerospace technology and urban infrastructure is driving the emergence of Urban Air Mobility (UAM) and autonomous airliners, reshaping the future of air transportation. UAM refers to the use of electric vertical takeoff and landing (eVTOL) aircraft to provide efficient, low-emission air travel within and around cities, aiming to alleviate ground traffic congestion and reduce travel times [1]. Simultaneously, the development of autonomous airliners (capable of operating with minimal or no human intervention) is gaining momentum, promising increased safety, operational efficiency, and cost-effectiveness in commercial aviation [2]. Together, these innovations mark a significant shift toward smarter, more sustainable air transportation systems, supported by breakthroughs in Artificial Intelligence (AI), sensor technology, and regulatory evolution.

As the skies grow increasingly crowded with traditional aircraft, drones, and emerging eVTOL vehicles, modernising Air Traffic Management (ATM) systems becomes essential. Traditional ATM frameworks, designed for conventional aviation, are not equipped to handle the complexity and volume introduced by UAM and autonomous operations [3]. To address this, the development of Unmanned Traffic Management (UTM) has emerged as a complementary solution, enabling the safe, scalable, and efficient integration of low-altitude, autonomous air traffic into national airspace systems [4]. UTM leverages digital communication, real-time data sharing, and dynamic airspace access. Together, ATM and UTM form the backbone of future-proofed aerial ecosystem, ensuring safety, reliability, and coordination across all types of airborne vehicles.

Integrating UTM into existing ATM infrastructure presents a range of technical, operational, and organisational challenges [4]. Traditional ATM systems are already under pressure, with many countries facing a critical shortage of air traffic controllers (ATCOs): an issue that hampers the capacity to manage even current levels of air traffic safely and efficiently [5]. Adding to this challenge is the rapid growth of unmanned aerial system (UAS) and UAM operations, which introduces unpredictable flight patterns, higher traffic density in low-altitude airspace, and the nead for real-time, automated coordination [6]. These factors demand that UTM systems be not only interoperable with legacy ATM systems, but also highly robust, adaptive, and capable of autonomous decision-making. Ensuring seamless integration while maintaining safety, realiabiity, and trust across both manned and unmanned aviation domains remains a core hurdle in realising the potential of next-generation air mobility.

2 Future of AI in ATM

In this paper, we will be discussing about the AI technologies that directly address the core challenges in airspace management and the increasing workload and staffing shortages faced by ATCOs.

2.1 Efficient Flight Planning

Efficient flight planning is a cornerstone of modern ATM, particularly as global air traffic continues to grow and demands on limited airspace intensify. Civil aviation flight plans are developed under instrument flight rules (IFRs) and must consider capacity constraints, aircraft performance limitations, and airline preferences. However, even though flight plans are typically filed about an hour before departure, they are often not executed as planned due to factors such as adverse weather, ground congestion, and delayed arrivals [7]. These disruptions reduce airport efficiency and propagate delays throughout the air traffic network, a phenomenon often referred to as the ripple effect [8].

Traditional ATM research has largely focused on tactical-level solutions such as flow management, but there is growing recognition that strategic-level flight planning alsoplays a crucial role. The works of Rosenow et al. [7] and Ye et al. [8] offer promising approaches to solving strategic flight planning challenges using optimisation and AI.

Rosenow et al. [7] identify that conventional flight planning still heavily relies on manual processes and heuristic methods that do not fully account for the dynamic and multi-objective nature of the airspace environment. As a result, suboptimal routes are often chosen, leading to excessive fuel consumption, extended flight times, and increased emissions. To address this, the authors propose a multi-objective optimisation model that balances multiple goals while maintaining logical route structures and time constraints. These goals include minimising fuel use, reducing delays, and maximising airspace utilisation. The results demonstrate significant potential for AI-driven models to improve operational efficiency and environmental sustainability.

Similarly, Ye et al. [8] propose a strategic flight planning framework tailored to high-demand, weather-sensitive regions in China. Their model optimises flight scheduling with two objectives: (1) minimising total departure and arrival time offsets (Flight Minimum Shift (FMS)), and (2) reducing strategic operational costs, including ground and airborne components (Flight Minimum Cost (FMC)). Using real-world data from rainy and foggy seasons at Chengdu Shuangliu International Airport (CTU), Tengchong Tuofeng Airport (TCZ), and Dehong Mangshi International Airport (LUM), the model showed that rerouting flights to less congested airports like LUM during capacity constraints at TCZ is both feasible and cost-effective. This effectively reduces the decision-making burden on ATCOs.

While these models highlight the effectiveness of optimisation in strategic planning, their real-world deployment faces challenges. Current models are often constrained by limited datasets and simplifications that fail to capture the full complexity of live airspace operations. As UAS and UAM begin to integrate into civilian airspace, such as those using vertiports (e.g., Munich International Airport, Figure 1), the need for more robust, adaptive, and AI-powered optimisation frameworks becomes critical. Future systems must be capable of dynamically coordinating mixed traffic environments with both manned and unmanned aircraft, all while managing growing complexity and operational uncertainty.

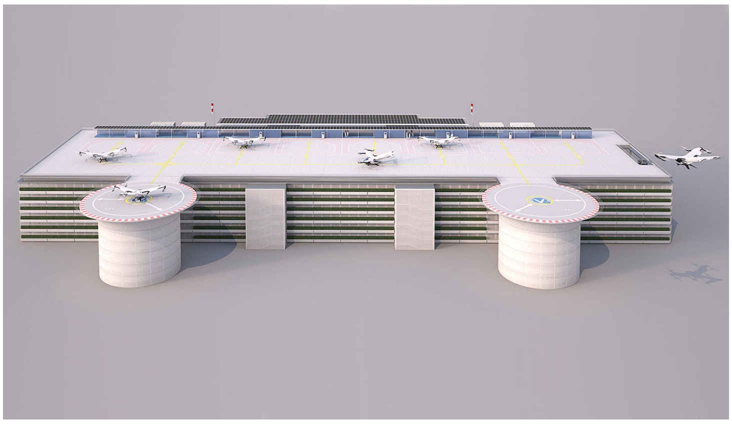


Figure 1: Development of vertiport on a parking garage at Munich International Airport [9].

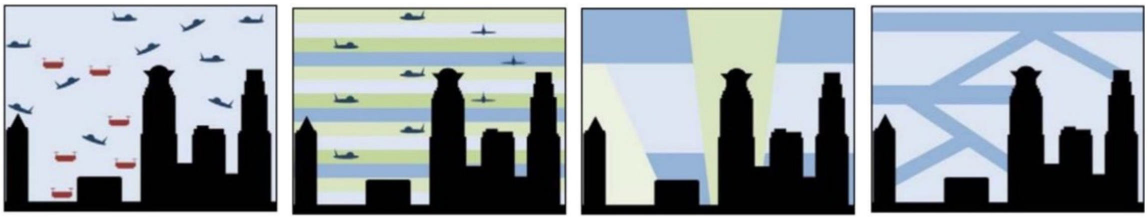
2.2 Maximised Airspace Utilisation

The increasing demand for UAM and the integration of unmanned aerial vehicles (UAVs) into controlled airspace present major challenges for traditional ATM. To maximise the use of limited urban airspace while maintaining safety and efficiency, novel airspace design concepts and AI-driven separation management techniques are being explored.

2.2.1 Metropolis Project: Structuring the Airspace

The first Metropolis project investigated how different airspace structures affect capacity, complexity, safety, and efficiency in high-density urban environments. It introduced four airspace concepts: Full Mix, Layers, Zones, and Tubes, each offering varying levels of structure to manage UAV traffic (Figure 2):

- **Full Mix:** An unstructured airspace where aircraft navigate based only on physical constraints such as terrain and weather.
- **Layers:** Vertically segmented bands that restrict aircraft heading directions, providing horizontal deconfliction through altitude separation.
- **Zones:** Airspace divided based on city layout, resembling current manned airspace practices.
- **Tubes:** Predefined, fixed aerial corridors that create conflict-free zones for structured traffic flow.



(a) Full-Mix (b) Layers (c) Zones (d) Tubes

Figure 2: Metropolis: Airspace concepts [3].

In simulations performed by Sunil et al. [10], conflict resolution was handled by the Modified Voltage Potential (MVP) algorithm in the Full Mix, Layers, and Zones concepts. In Zones and Tubes, A* algorithm was used to determine the shortest trajectory prior to departure. Despite the structured nature of Tubes, it failed to meet traffic demand due to limited flexibility.

The results showed that less-structured concepts (Full Mix and Layers) provided better traffic distribution, leading to fewer conflicts and higher efficiency. Layers, in particular, achieved the lowest number of separation violations while maintaining high throughput and route efficiency. This indicates that moderate structuring, rather than rigid corridor enforcement, optimally balances safety, capacity, and efficiency in nominal high-density scenarios.

2.2.2 Metropolis 2 Project: Separation Management Strategies

Building on these findings, the Metropolis 2 project explored ATM concepts for mixed airspace environments, including both open and constrained regions. This second phase addressed practical constraints such as tall urban buildings and complex terrain, where vertically layered airspace may be impractical (e.g., in cities like New York).

The project compared three separation management strategies with varying degrees of centralisation (Figure 3) [11]:

- **Centralised:** A single central authority handles pre-flight planning and strategic conflict resolution using global knowledge of all flights.
- **Decentralised:** Each UAV is responsible for its own trajectory and separation, without access to other flight plans.
- **Hybrid:** Combines strategic central planning with tactical in-flight deconfliction by the agents themselves (a mix of both centralised and decentralised concepts).

Figure 3: Metropolis 2: Air traffic control concepts [12].

According to Badea [12], the simulations revealed that each concept has trade-offs. The centralised model achieved the highest route efficiency but lacked scalability. The decentralised model ensured fair access to airspace but struggled with conflict management. The hybrid approach provided the best safety performance and balanced traffic distribution, showcasing the benefits of combining proactive (strategic) and reactive (tactical) elements.

2.2.3 Implications for the Future of AI in ATM

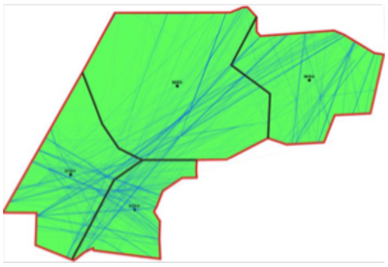
The findings of Metropolis and Metropolis 2 underscore the vital role that AI will play in the future of ATM. In particular:

- AI algorithms such as A*, MVP, and conflict resolution heuristics are critical for enabling dynamic, decentralised trajectory planning.
- Multi-agent reinforcement learning (MARL) and predictive models could further enhance the hybrid model by learning optimal conflict-avoidance behaviours in real time.
- Strategic AI planning systems are needed to anticipate demand surges, optimise vertical and horizontal traffic flow, and ensure robust safety margins under uncertainty.

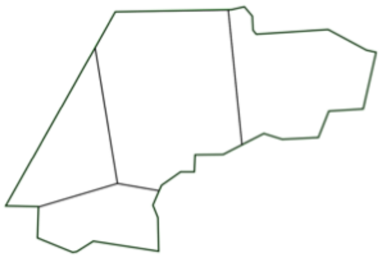
2.3 Dynamic Airspace Sectorisation

Dynamic Airspace Sectorisation (DAS) is a responsive approach to airspace management that adjusts sector boundaries according to real-time traffic demand and capacity constraints [13]. By clustering traffic patterns to identify high-density areas, DAS aims to support efficient planning and enhance controller operations [14]. The key objective is to adapt sector configurations dynamically, in a time-dependent manner, to better match actual operational needs.

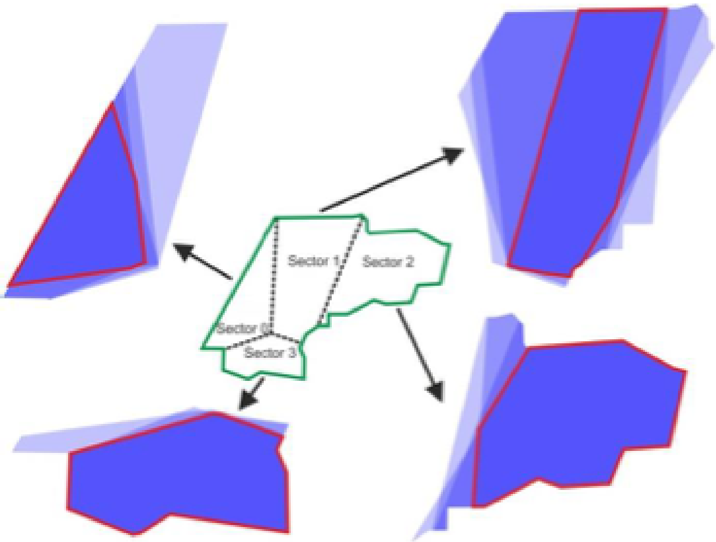
Early research on optimising airspace structure applied evolutionary algorithms (EAs), focusing on balancing controller workload through several operationally relevant metrics, such as the total and standard deviation of task load, geometric coherence of sector shapes and number of flight path intersections caused by sector boundaries [14]. This approach successfully reproduced existing operational sector designs, such as those in the EDDYDUTA area (Figures 4a and 4b), without relying on expert knowledge. It also demonstrated adaptability to fluctuating daily traffic patterns (Figure 4c).



(a) Original airspace structure



(b) Sectorisation after DAS optimisation



(c) Dynamic adaptation to traffic demand

Figure 4: Airspace EDDYDUTA [14]

Recent research explores deep learning to enhance DAS, offering greater scalability and predictive accuracy than traditional EAs. Zhou et al. [15] introduced a multi-task learning (MTL) model using bidirectional long-short term memory (Bi-LSTM) networks to predict both traffic flow and airspace capacity. This model supports proactive sector adjustments based on traffic-capacity imbalance forecasts across multiple time horizons. While effective, the Bi-LSTM model is a black-box system, which limits its operational acceptability due to the lack of transparency in how predictions are derived.

To address this, Zhou et al. [13] proposed a more interpretable AI framework called AirFusion, which integrates the Temporal Fusion Transformer (TFT) for time-series forecasting. The model predicts airspace demand and capacity up to four hours in advance while respecting operational constraints imposed on air traffic controllers. It incorporates Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering to identify major traffic flows and constructs weighted graphs to inform sectorisation decisions. Results show high predictive accuracy, with mean errors of 0.0234 (demand) and 0.0291 (capacity), and R-squared values of 0.9133 and 0.9605, respectively. Clustering results are shown in Figure 5, where flight trajectories are color-coded, and major flows within each cluster are indicated by thickened lines. When demand exceeds sector capacity, sectors are subdivided (purple dashed lines) to maintain manageable workloads.

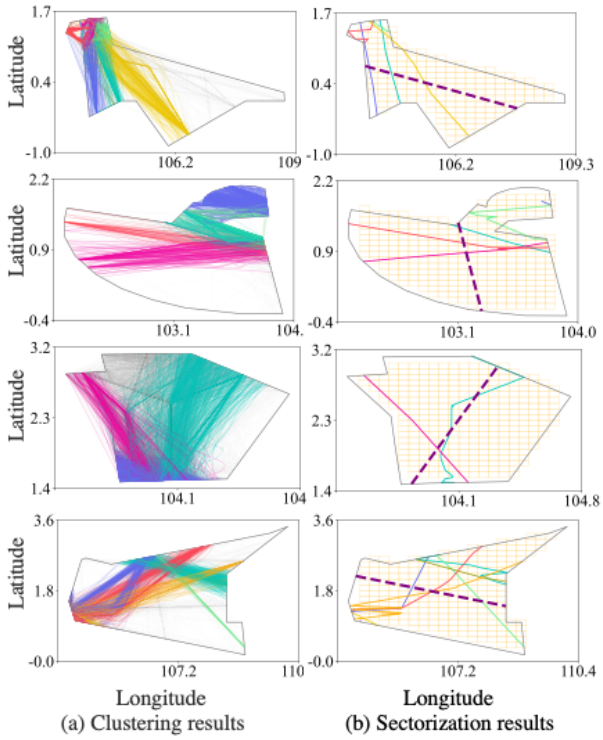


Figure 5: Clustering and sectorisation results for selected sectors [13].

Compared to the earlier Bi-LSTM approach, the TFT-based model offers better interpretability, thanks to integrated feature selection and attention mechanisms. This makes it more suitable for operational deployment, where trust and explainability are critical for controller acceptance.

2.4 Digital ATCO Assistant

While AI has introduced numerous benefits in ATM, the current interfaces for air traffic control (ATC) remain largely passive, limited to information provision. Decision-making and high-cognitive-load tasks still rely heavily on human ATCOs. To meet the increasing demands of global air traffic, a shift toward higher automation levels in ATC systems is essential. This transition requires a redefinition of task distribution between human controllers and AI-based assistants.

Jameel et al. [16] propose a digital ATCO architecture combined with a Human-Autonomy Teaming (HAT) interface, forming key components of a highly automated controller working position (CWP) for en-route traffic. The digital ATCO is designed to handle time-intensive tasks such as conflict detection and resolution, generating advisories and commands, and communicating with pilots. This enables human ATCOs to adopt a supervisory role, potentially reducing the requirement from two to one human controller per sector.

The HAT interface plays a central role by providing an intuitive interaction mechanism between human operators and AI systems. It supports three modes of control: human, hybrid, and autonomous, ensuring flexibility and maintaining human oversight.

Figure 6 illustrates the architecture, which consists of the following core components:

1. Controller Display and Simulation Tool (CoDiST): a radar display system supporting primary ATCO tasks.
2. Digital Interactive Radar Controller (DIRC): the digital ATCO responsible for traffic control, action planning, and execution.
3. HAT Interface (HI-DIRC): the HAT interface enabling communication between human and digital ATCOs.
4. Data And Service Integration Module (DASIM): a data integration system ensuring seamless information access.
5. Various support tools including:
    - Trajectory Generation and Advisory Tool (TraGAT): for generating optimised flight trajectories.
    - Trajectory Conflict Checker (TCC): for continuous trajectory conflict checks.

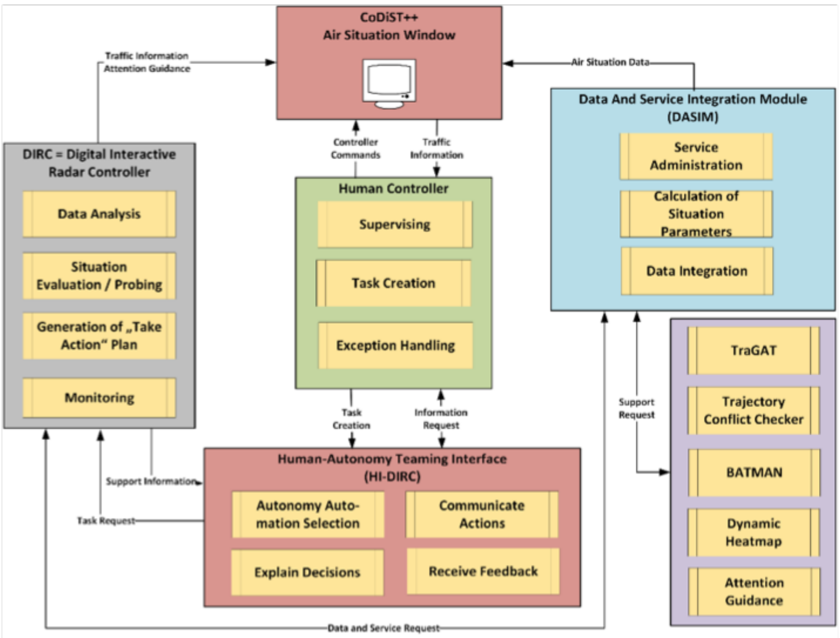


Figure 6: Overview of the system that enables single human ATCO assisted by a digital ATCO. [16]

- Boundary Arrival Task Manager (BATMAN): for coordination and handover readiness.
- Dynamic HeatMap (DHM): for detecting sector congestion and hotspots.
- Attention Guidance (AG): for highlighting critical flight events on the radar.

A proof-of-concept CWP was showcased at Airspace World 2023, where it received positive feedback. Professional ATCOs expressed particular interest in shaping further development and validation of the system.

Looking ahead, future research will focus on task allocation strategies to maximise efficiency gains from automation while ensuring operational safety. This includes identifying which tasks provide the highest benefit when delegated to AI, refining human-in-the-loop control strategies, and ensuring seamless reallocation of tasks from digital ATCO back to humans under uncertainty or failure conditions. Emphasis will also be placed on increasing the transparency and explainability of AI decision-making to build trust and support certification for operational deployment.

3 Challenges of AI in ATM

4 Conclusion and Outlook

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