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Autonomous Separation Management System for Drones Through Optimal Layer Interactions

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***Abstract*—In the coming decades, drones are expected to operate within urban areas at high volumes, and if implemented successfully, applications such as infrastructure inspection, medical supply and parcel delivery can be improved by the technology. This poses a challenge: how are these drones to be guided in this highly-constrained airspace? Many existing projects have approached the problem from different angles: some place more importance on the Tactical Layer and thus resolving conflicts in flight, while other research focuses on the Strategic Layer with scheduling or airspace design. While analysis is done on a complete system, with all separation management layers implemented, work remains to be done regarding quantifying how these layers interact, and what positive characteristics of these interactions can be utilised to make the system more efficient, safe, and robust to uncertainties. This paper proposes a framework on which this analysis can be performed. Firstly, layers are investigated independently. A feedback system is proposed, where layer outputs are measured, as is the resulting system performance. For instance, an initial hypothesis is that reducing airspace complexity in the Strategic layer, while accounting for uncertainty, will lead to better overall system performance. This can help with minimising flight times and improving overall safety. Also, manoeuvres performed by the Tactical (in-flight) layer should take this complexity metric into account. The feedback loop approach also proposes that the complexity be fed back to the central planner, and that the Strategic (Pre-Flight) layer should be able to take system status into account when performing planning.**

***Keywords*—drones, layers, system, interactions, U-Space, ATM**

I. Introduction

In the coming decades, drone traffic is expected to reach unprecedented densities, never before seen in classical aviation. Projections [1] estimate that the number of drones, flying primarily in urban airspace, will number 7 million by the year 2050. Applications will include parcel delivery for medical [2] and commercial purposes, as well as infrastructure inspection and first response. The highest densities are expected to come from parcel delivery, as companies such as Amazon [3] with their Prime Air drone delivery project are looking to leverage large volumes in order to make the venture economical. In order to guarantee that this growth occurs responsibly, the aspects of U-Space need to be considered and developed thoroughly, maximising not only efficiency but also safety. In order to do this, Separation Management, or the set of actions taken to ensure safe distances between drones at all times, need to be a solved issue come implementation. Separation management in urban very-low-level airspace (U-Space [4] is a well-researched topic. On a European level, large-scale projects such as Metropolis II [5] investigate the U-Space implementation on a large scale, designing concepts that cover everything from airspace design to conflict avoidance algorithms. Works such as M. Ribeiro's [6] focus in depth on innovative methods such as Reinforcement Learning to determine the optimal Conflict Avoidance manoeuvres, showing their promise when compared to traditional geometric methods. The goal of this research is to determine the optimal methods for Separation Management, that is the action of keeping all aircraft at a safe distance from each other at all times in a way that is stable in time. A separation management system is then broadly defined as a combination of layers [7] that work together to achieve this goal. These can be seen in Figure 1.

The Strategic layer encompasses aspects such as airspace design, route generation and flight scheduling. Here, the goal is to provide a structure to the airspace and to the flights themselves and ensure that they remain stable. Such a layer is the most prone to uncertainties: in a practical operational environment, there will always be deviation from the schedule at hand, and flight routes will not always be flown as defined. Thus, the layer must provide solutions that are robust to uncertainty to ensure system stability. Should uncertainties arise, the Tactical Layer is utilised to manage separation. This layer is triggered when the drones are already in flight, and applies manoeuvres to avoid conflicts. Some concepts in classical Air Traffic Management argue for full decentralisation, namely the

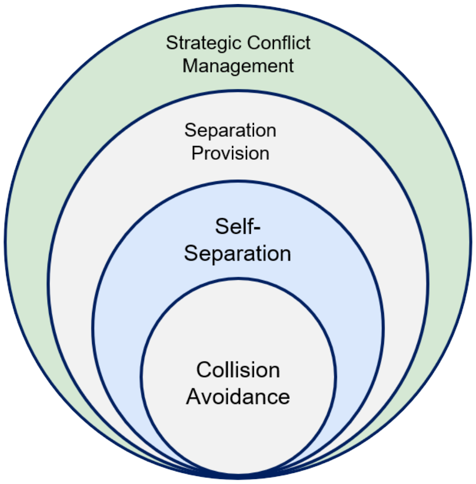

Figure 1. Separation Management System Layers, adapted from [7]

Free Flight concept [8]. This concept relies on the Tactical Layer and resolves conflicts using geometric methods such as the Modified Voltage Potential (MVP). While the flights are unstructured, this method theorises that stability will ensue as all aircraft are following the same set of rules. While concepts such as free-flight are promising in open airspace [8], and will likely be of great value for drone traffic outside urban centers, urban environments pose a greater challenge since decentralised conflict avoidance methods are affected by the geometrical constraints of low buildings and terrain in very-low-level (sub-250 meter flight ceiling) airspace. Since this low-level airspace stipulated in the U-Space [9] [4] documentation, efforts must be made to adequately deal with these constraints. Projects such as Metropolis II [5] have taken this into consideration by implementing a street-network inspired route graph, along which movement is constrained in one-way lanes. Metropolis II [5] also compares several concepts with different levels of centralisation (thus planning done by a centralised agent), and shows the potential for a ”hybrid” approach, where the strategic layer is centralised and tactical and detect-and-avoid are performed in-flight by the drone.

II. Methodology and Research Framework

The methodology used in the further stages of the work is outlined in this section. The preliminary model of a feedback-based separation management system is presented, followed by an outline of possible methodologies for the layers at hand.

A. Preliminary Model

The preliminary model for the Autonomous Separation Management System will follow the layers defined in Figure 1. A feedback loop will be implemented: the strategic planner will rely on feedback from measured airspace complexity, route flexibility [10] and robustness. The envisioned implementation is seen in the flowchart under Figure 2.

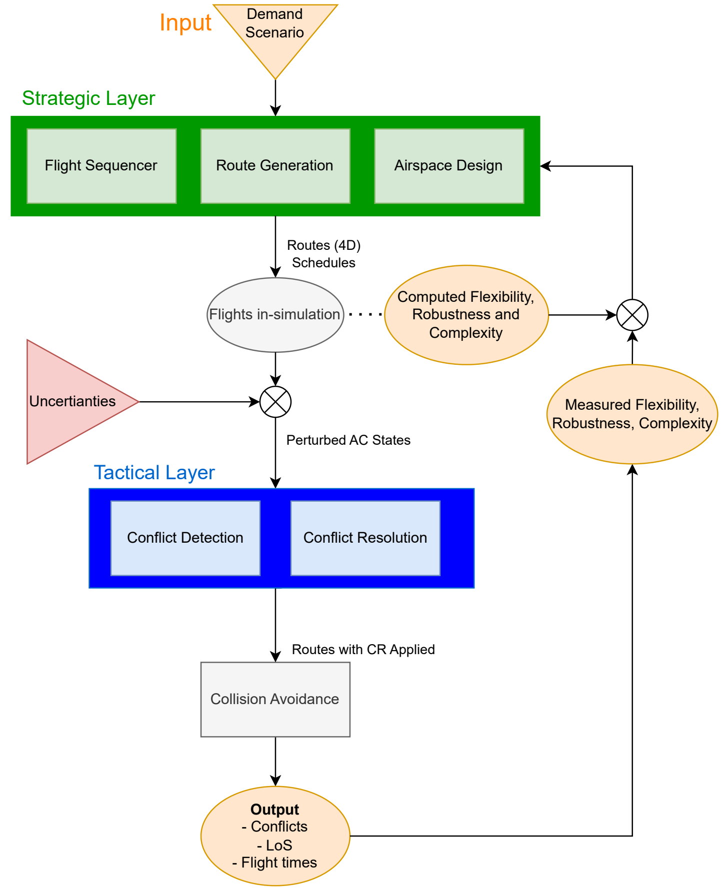

Figure 2. Separation Management System Feedback Model

In this figure, the Green layer represents the Strategic Layer, and contains flight sequencing, route generation and airspace design. For the Tactical, or Self-Separation layer, conflict detection and resolution are the main blocks to implement. To elaborate upon this, demand scenarios are used as input. The Strategic Layer is comprised of a Flight Sequencer, Route Generation and Airspace Design modules. The reason that these are kept as blocks is that the configurations of these are going to be varied. For instance, the flight sequencer could apply demand capacity balancing using Mixed-Integer Programming, or in fact utilise a Reinforcement-Learning-trained model for the flight planning. Likewise, the Route Generation module can be selected in the same way. For airspace design, the vision is that works such as M. Ribeiro’s [11] can be used as inspiration for a dynamic airspace reconfiguration tool based on Reinforcement Learning. The difference here is that not only the Conflicts, Losses of Separation and other statistics such as cumulative delay can be used in the reward function, but that the system learns policies that minimize airspace complexity and improve stability through the usage of robust and flexible [10] routes and plans. This will be done by computing complexity before and after disturbances to evaluate the efficacy of the Tactical Layer. For the Strategic Layer, its performance will be assessed without taking the Tactical Layer into account.

The elements and metrics used in the feedback loop will be analysed for effectiveness on the same demand scenarios in the BlueSky [12] ATM simulator. In order to implement the system, the methodology behind the layers themselves (and thus the underlying methods) must be selected. Available methodologies are numerous, and are discussed in the next section.

B. Layer Implementations

For each of the layers of the Separation Management System, as seen in Figures 1 and 2, there is a multitude of possible implementations. For the Strategic and Tactical layers, some possible methodologies and implementations are listed:

- **Strategic Layer**
  - *Scheduling Methods:* Mixed-Integer Programming, Brute-Force, Genetic Algorithm, Simulated Annealing, Particle Swarm or other
  - *Airspace Design [13]:* Full-Mix, Layers, Zones, Tubes or other
  - *Route Generation:* Dijkstra's Algorithm, A*, Branching-Continuous [14] or other
- **Self-Separation/Tactical Layer:**
  - Modified Voltage Potential, Reinforcement Learning-based or other

Important to acknowledge is the fact methods combining several aspects exist. These include works such as those by D. Sacharny [15] with the "Algorithm SD" (Strategic Deconfliction) and W. Dai [16], where airspace design and 4D scheduling (thus routes taking a time element into account) are both encompassed within the methodology.

Machine Learning models are often used in the context of Air Traffic Management research. Reinforcement learning specifically has been used in several contexts, namely to reconfigure the airspace [11], improve merging maneuvers and even Conflict Resolution strategies. These techniques will also be leveraged in this project. These will be implemented and researched, especially in the context of the Strategic layer, for schedule modification and airspace reconfiguration based on system complexity feedback, as seen in Figure 2.

In order to assess the system designed, and evaluate system and layer performance, Fast-Time simulations will be performed in the BlueSky [12] Open ATM simulator. This versatile Air Traffic Management simulator is expandable through Python plugins, allowing for fast testing, easy integration with other software, and most importantly, reproducibility of results, as it is entirely open-source and therefore available for all users. This also aims to solve a common pitfall in Air Traffic Management research: the lack of a performance benchmark. Most well-performing methods are compared separately and for different air traffic scenarios. Thus, everything can be proven to work. The idea here is that through keeping code and scenarios freely accessible, a platform is provided where direct comparison with other methods ceases to be a chore.

C. Fast-Time Simulation and Environment Setup

In order to assess the system, fast-time simulations will be run in the BlueSky [12] ATM simulator. An urban environment is then simulated using data from OpenStreetMap [17] (OSM), by importing all potential delivery locations, as well as building heights and geometry, street networks and hospital locations (among other data). This is done with a self-contained plugin for BlueSky, which obtains data from the Overpass [18] API. The user provides the bounding box of the test area, or the city name as a string, and the plugin can import all of the necessary data automatically. This is done in an effort to help faster scenario generation to be used for Reinforcement Learning, where generalizability is paramount (thus testing and training on a variety of city topologies is needed). Currently, buildings need to be avoided for drone operations - the plugin automatically imports and loads the buildings above an input height and displays them as geofences in BlueSky.

Then, an adaptation of D. Rein-Weston's [14] method is used to plan routes around the resulting geofences. An example of the resulting scenario is seen in Figure 3.

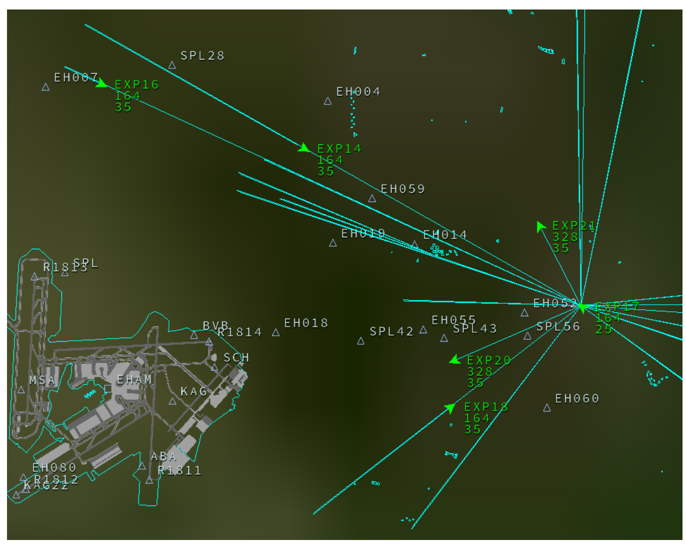

Figure 3. Amsterdam Environment With Geofences in BlueSky [12] ATC simulator

The simulation setup will be further improved through including and improving the following features:

- **Terrain** import, automated from open-source data.
- **Discrete** route network generation as a graph, to better test classical optimization methods and allow for fast conflict detection for en-route conflicts when strategic planning is performed.
- **Uncertainty** modelling for the takeoff delays
- **Battery Model Plugin** for eVTOL and quadcopter drones, to be used as an optimisation parameter

Another important project is the creation of an AI Gymnasium [19] environment for benchmarking Reinforcement Learning approaches in BlueSky. The implementation will be done in the coming months.

III. Conclusion

This paper presents the envisioned methodology for assessing layer interactions in an Autonomous Separation Management System for Drones. Then, the process is continued through optimising these in order to create a system framework that provides robust and flexible scheduling to allow for effective conflict resolution in the tactical layer, should uncertainties arise. Likewise, the Tactical layer's outputs are assessed in terms of the stabilising effect on the system complexity - a return to the computed schedule is desired in order to keep predictability high. In summary, the layer interactions are to be tested extensively using a feedback loop approach, including the difference between predicted and measured complexity. There are some challenges regarding the implementation of Reinforcement Learning training scenarios within BlueSky - no standard benchmark exists, and a plugin implementation can be slow. These issues are currently being worked on, through the design and implementation of a standardised testing environment for RL and AI application in the BlueSky ATM simulator. As for the other components, the basics of the urban environment data import, route generation and scheduling have been implemented. Thus, the immediate focus will be to design a complexity-sensitive Strategic Layer, and quantify to what extent route and metrics such as plan flexibility and robustness can be used in the system's feedback loop to improve overall safety, efficiency and stability through complexity reduction.

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