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RL-based Scheduling of an AAM Traffic Network

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***Abstract*—This study presents an approach for pre-flight planning process to be used in the future Advanced Air Mobility (AAM) system especially after contingency situations and relevant activities take place. The methodology for scheduling is modeled as a reinforcement learning (RL) agent that resolves potential conflicts for the traffic and balances the demand and capacity at vertiports. The reason behind to use RL is that specific problem requires a very quick response since it also deals with resolving conflicts that are observed between the flights that are about to take-off and the contingent flights that diverted for an emergency landing. The main objective of this work is to develop a pre-flight planning service to work compatible with contingency management activities for enhancing the contingency management process for the AAM system.**

***Index Terms*—AAM; UTM; pre-flight planning; potential conflict resolution; demand capacity balancing; contingency management; reinforcement learning**

I. Introduction

The air transportation system is envisioned to incorporate the Advanced Air Mobility (AAM) system by extending its operations to sub-urban, urban, and rural areas and promising more flexible, accessible, and agile service to its users. One of the most important challenges to enable AAM is safety. For providing safety to the system a proper contingency management (CM) concept has to be defined and relevant services have to be developed and coordinated with CM activities. One of these services can be pre-tactical replanning since mitigating potential conflicts in pre-tactical phase is much more safer than solving in tactical phase. That service aims to re-schedule the flights at pre-tactical phase that may be interrupted by CM activities of other flights. Fig. 1 represents an example where the pre-flight replanning is required. This service can also serve as an initial flight plan scheduler.

Studies up to date focus on the strategic planning of the Unmanned Aircraft System Traffic Management (UTM) by considering strategic conflict resolution [1]–[3] and demand capacity balancing (DCB) problem [4]–[6]. Our optimization-based solution of the pre-tactical replanning service is elaborated in [7].

This paper presents a service which intends to schedule/reschedule the flights that did not take-off yet and are conflicted by the flights that changed their routes due to adverse conditions. Main reason to use reinforcement learning (RL) is that the problem requires a quick recovery since the affected flight plans might be about to take-off. The RL agent considers multiple aspects such as the conflict resolution of the flights and DCB at vertiports.

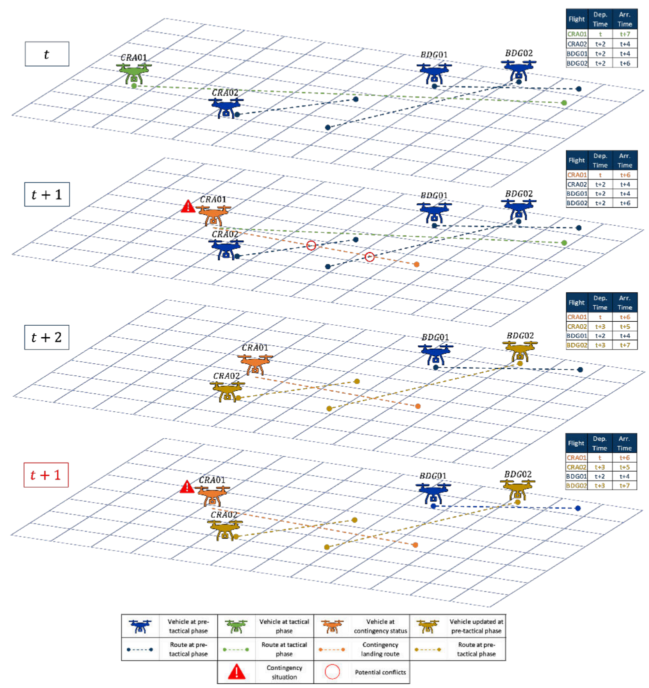


Figure 1. Representation of the pre-flight replanning.

II. Methodology

A centralized RL-agent is used to resolve potential conflicts and balance the capacity usage within the generated AAM traffic.

An action set that includes eight discrete actions for each individual flight f_i is defined as $\mathcal{A}^{f_i} = \{0, 1, 2, 3, 4, 5, 10, 15\}$ which represents the ground delay options in minutes. The defined action set can be represented as follows:

$$\mathcal{A} = \left[\left\{ \mathcal{A}^{f_i} \right\}_{f_i \in F} \right]^T \tag{1}$$

where $F = \{f_1, ..., f_N\}$ is the set that includes all flights.

The observation space formed as a vector that includes departure times of each flight $\{f_{i,dep}\}_{f_i \in F}$ where $f_{i,dep}$ is the departure time of flight f_i and the total number of conflict

X within the traffic network. The observation set is given as follows:

$$\mathcal{O} = \left[\{f_{i,dep}\}_{f_i \in F}, X \right]^T \tag{2}$$

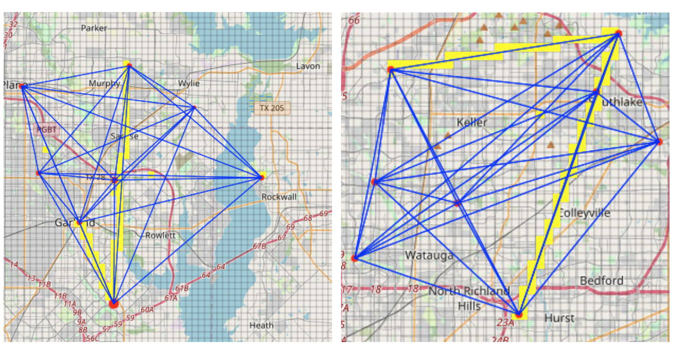
The reward function is designed to resolve conflicts that are observed by considering the capacity throughput of vertiports and minimization of the total ground delays given. The reward scheme is defined as below:

$$\mathcal{R} = \begin{cases} -10, & \text{if } D_{v,tw} > C_{v,tw} \\ -10, & \text{if } X > 0 \\ 5e^{-0.002 \frac{\sum_{i=1}^{N} d_{f_i}}{N}}, & \text{otherwise} \end{cases} \tag{3}$$

where $D_{v,tw}$ and $C_{v,tw}$ are respectively the total demand and capacity at vertiport v in time window tw. The ground delay given to the flight f_i is represented as d_{f_i} and N is the total number of flights within the traffic. For the training phase, proximal policy optimization (PPO) algorithm is used to benefit from its efficiency and output scalability.

III. Case Study

For the tests, various AAM traffic networks with different sizes ranging from 80 flights to 250 flights are generated. The size of the observation space is set by considering the maximum number of flights and for the rest of the set dummy flights are included that does not create any conflicts and does not have an effect on vertiport capacities, therefore does not require any additional delay. A couple of examples of the generated traffics with observed conflicts are given in Fig 2.



(a) Sample traffic I. (b) Sample traffic II.

Figure 2. Different sample traffics with different sizes that are generated around Dallas - Fort Worth area including both strategic and pre-tactical conflict cases. Vertiports are in red, routes are in blue, and conflicts are given in yellow. Cell size of the grid map is 500 m. as length and 50 m. as height.

A traffic with 126 flights is picked as a test case for scheduling by considering potential conflicts and capacity throughput. Number of observed conflicts at the beginning of the case is 109. Given ground delays by the RL agent and how many vehicles are affected can be seen in Fig. 3. The average ground delay given is observed as 4.65 minutes per flight and the standard deviation is 5 minutes. Additionally, 94.50% of the conflicts are resolved.

Even though all the conflicts are not resolved, results indicate that the RL agent shows a good performance on

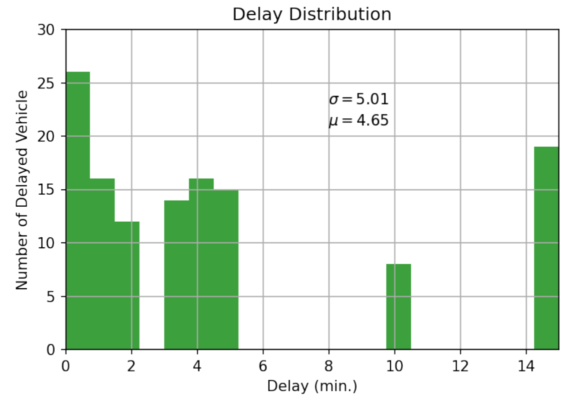


Figure 3. Distribution of the given ground delays after conflict resolution.

scheduling the AAM traffic. Especially, providing a quick response for the traffic is the key part for the flights about to take-off. Yet, the model improvements can be extended by more training or by developing the reward structure, to resolve all the conflicts and provide ground delays efficiently.

IV. Conclusion

This paper explores the development of an RL-based scheduling service to be used in mitigation of potential conflicts including between flights that deviate from their routes in tactical phase and flights that are in their pre-tactical phase. The developed service covers not only potential conflict resolution but also DCB which makes it suitable to be used in initial flight scheduling problem as well. Possible improvements can be turning centralized approach to a decentralized one with multi-agent RL structure for more efficient scheduling process. Moreover, traffic size can be increased to properly show RL's impact on such problem and different action sets such as latitude, longitude, and altitude change alongside ground delay can be explored.

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