Evaluating UAM Route Feasibility in Terminal Airspace via Probabilistic Aircraft Trajectory Prediction

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Extended abstract submitted for presentation at the Conference in Emerging Technologies in Transportation Systems (TRC-30)
September 02-03, 2024, Crete, Greece

April 15, 2024

Keywords: Urban Air Mobility, Terminal Airspace, Normalizing Flows, Trajectory Prediction

1 INTRODUCTION

While Urban Air Mobility (UAM) holds promise for improving urban travel, its integration with existing Air Traffic Management (ATM) systems poses significant challenges. As UAM technology evolves and more VTOLs enter shared airspace, ensuring interoperability with ATM becomes increasingly complex (Levitt *et al.*, 2023). One cautious approach is to design exclusionary airspace for UAM, simplifying management but potentially limiting operational capabilities. Vascik *et al.* (2020) emphasized the need for balance, where excluding UAM operations from airspace used by ATC limits available airspace, especially at higher altitudes. Similarly, simulations in the Dallas-Fort Worth area reveal challenges in achieving separation between UAM and conventional aircraft, even with well-designed corridors (Lee *et al.*, 2022).

As operational tempo increases and UAM technology progresses, there will be an increasing requirement for coordination between UAM and ATM operations. This coordination becomes crucial as automation capabilities are developed and sufficiently validated beyond UML-4 (Levitt *et al.*, 2023). Despite its promise, relatively few studies have examined the feasibility of integrating UAM operations within airspace, especially in regions with complex flight patterns.

One key aspect of safely integrating UAM with ATM is accurate prediction of non-UAM conventional aircraft trajectories to mitigate collision risks and to ensure necessary separation between UAM and conventional aircraft. While conventional aircraft typically follow predefined routes, uncertainties can arise especially in terminal airspace due to heavy traffic, aircraft dynamics, environmental conditions or human factors.

To this end, we propose a framework for assessing the feasibility of UAM routes near terminal airspace by leveraging probabilistic aircraft trajectory prediction. Our framework utilizes short-term predicted trajectory distribution information generated by a flow-based deep-generative model, called Normalizing Flows. This information is used to evaluate UAM routes intersecting ATM airspace at various altitudes, with UAM aircraft to decelerate by anticipating encounters with conventional aircraft in the short term.

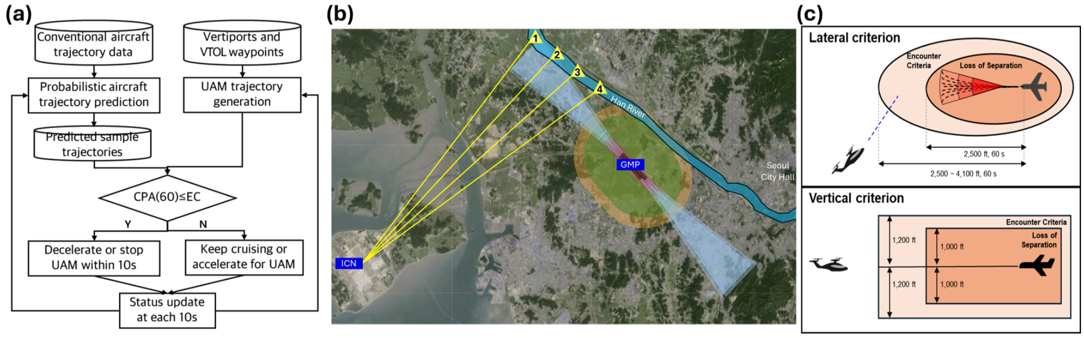

Figure 1 – *(a) Block diagram of the proposed framework; (b) Study area illustration; (c) Concept of 'encounter' in our study*

2 METHODOLOGY

We simulate UAM aircraft to traverse airspace that is traditionally used for arrival and departure procedures to assess the feasibility of incorporating UAM into existing ATM operations along specific UAM routes (lanes). We use conditional Normalizing Flows as the probabilistic trajectory prediction model, described in Section 2.1. In the simulation, we begin by generating predicted sample trajectories of conventional aircraft using the trained conditional Normalizing Flow. The speed of UAM vehicle is adjusted following the control scheme, described in Figure 1 (a) and in Section 2.2, based on the predicted sample trajectories of conventional aircraft and planned trajectories of UAM aircraft. We make two key assumptions: 1) UAM aircraft maintains a constant cruising speed of 130 mph (210 km/h), and 2) UAM aircraft follows a linear path from a vertiport to predefined lanes at specified altitudes every 10 seconds. Over a two-day period, we evaluated deviations from scheduled flight times and separations between UAM and non-UAM aircraft. This study focuses on the airspace over the western section of the Seoul Metropolitan area, including Incheon Airport (ICN) and Gimpo Airport (GMP). As shown in Figure 1(b), this airspace experiences heavy air traffic from airport arrivals and departures, posing challenges for future UAM flights aiming to connect ICN with central Seoul[1]. We present results for testing four lanes at four altitudes, aligning with the fastest route to the Han River, recognized as the main corridor for UAM operations in Seoul.

2.1 Probabilistic Aircraft Trajectory Prediction

Given a time stamp t, the location of an aircraft is denoted as $c_t = (\mathrm{lon_t}, \mathrm{lat_t}, \mathrm{alt_t})$, where $\mathrm{lon_t}$ and $\mathrm{lat_t}$ represent the longitude and latitude, and $\mathrm{alt_t}$ is the altitude. With H historical observations, $\mathbf{x}_t = [c_{t-H+1}, \cdots, c_t]$, our objective is to predict the conditional probability distribution of T future locations $p(\mathbf{y}_t|\mathbf{x}_t)$, where $\mathbf{x}_t = [c_{t+1}, \cdots, c_{t+T}]$. The trajectory data was collected via ground-based radar tracks over 7 consecutive days in May 2022 near Gimpo Airport (GMP) in South Korea. Training utilized data from May 24th to 28th, validation from May 29th, and testing from May 30th to May 31st. We used 60-second data for the observation $\mathbf{x}_t$ and the subsequent 60-second data for $\mathbf{y}_t$. Then, we selected the $\mathbf{x}_t - \mathbf{y}_t$ pairs where over 90% of the data points had altitudes exceeding 150 meters, to exclude instances related to ground operations.

The proposed prediction model consists of two sub-modules: a condition encoder and a flow-based decoder. The condition encoder takes the historical location as input and produces an encoded latent vector ($h_t = g(\mathbf{x}_t)$) using Gated Recurrent Units, following prior work (Choi *et al.*, 2021). Then, the flow-based decoder uses a stack of normalizing flows to transform a simple distribution $\mathbf{z} \sim \mathcal{N}(0, \mathbf{I})$ to $p(\mathbf{y}_t|\mathbf{x}_t)$, conditioned on the encoded latent vector computed by the condition encoder. The model is trained by maximizing the conditional likelihood of a

[1]Refer to this video clip for a more detailed view: `https://youtu.be/eV463hZ8cgM`

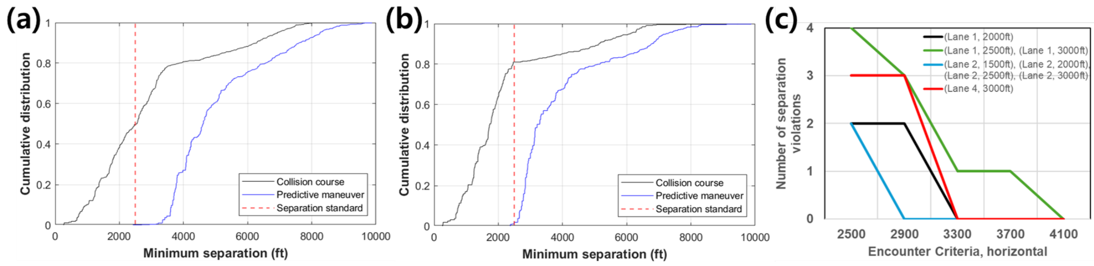

Figure 2 – *Cumulative distribution of minimum separation for (a)* $EC_h = 2500ft$ *and (b)* $EC_h = 4100ft$*; (c) Loss of separation for lane and altitude combinations given* EC_h

training dataset, $\mathcal{L}(\mathcal{D}) = -\frac{1}{|\mathcal{D}|}\sum_{(\mathbf{x}_t,\mathbf{y}_t)\in\mathcal{D}}\left[\log q_0(\mathbf{z}_0) - \sum_{k=1}^{K}\log\left|\frac{\partial f_i(\mathbf{z}_i|\mathbf{x}_t)}{\partial \mathbf{z}_{i-1}}\right|\right]$ where f represents the invertible (bijective) functions $f_i, i \in \{1, ...K\}$, i.e., $\mathbf{z_i} = f_i(\mathbf{z_{i-1}})$, thus $\mathbf{z_{i-1}} = f_i^{-1}(\mathbf{z_i})$. In this study, we used affine coupling layer for parameterizing the transformation f (Dinh *et al.*, 2016). See Dinh *et al.* (2016), Papamakarios *et al.* (2021) for details.

2.2 Speed Adjustment for UAM aircraft

From the trained model, we retrieved 1,000 sample prediction trajectories at each timestamp in the testing dataset (collected on May 30th and 31st). These samples represent the distribution of future trajectories given the past trajectory sequence. At each 10-second interval, the closest point of approach (CPA) between the planned trajectories of UAM and the predicted sample trajectories of conventional aircraft within the next 60 seconds, denoted $CPA(60)$, is calculated. The speed adjustment for the UAM aircraft is contingent upon *encounter*, which define situations where the horizontal separation falls below $EC_h \in$ 2,500 ft, 2,900 ft, 3,300 ft, 3,700 ft, 4,100 ft and the vertical separation decreases to less than $EC_v =$ 1,200 ft within the next 60 s, as seen in Figure 1(c) . Under encounter criteria, the UAM aircraft adjusts its status to 'decelerate' or 'stop' depending on the severity of the situation[2]. If deceleration is sufficient to avoid a near miss, it slows down to half its speed within 10 s. If stopping is necessary, it stops within the same time frame. Once the situation resolves, it switches to 'accelerate,' gradually increasing speed to half its cruising velocity within 10 s. Loss of separation (LoS) occurs if the CPA is projected to fall below a separation standard S, set at 2,500 ft horizontally and 1,000 ft vertically.

3 RESULTS

Figure 2 (a) and (b) illustrate the cumulative distribution of minimum separations[3] between conventional aircraft and UAM aircraft. The black curve represents scenarios without applying a deceleration maneuver, while the blue curve represents scenarios with the application of deceleration. In most cases, the proposed predictive approach maintains the separation standard of 2,500 ft. However, as shown in Figure 2(c), under specific encounter criteria, some cases result in less than 5 LoS cases, with its frequency diminishing with higher EC_h.

In Figure 3 (a), each group of bar chart illustrates the average minimum separations (*higher the better*) under different EC_h, categorized by lane and altitude combinations. In the case of (lane, altitude) = (3, 3000ft), the average minimum separations are 3,942ft, 4,393ft, 4,875ft, 5,550ft, and 5,906ft, for each EC_h, respectively. Across all cases, higher EC_h values correlates with increased average minimum separations, as UAM aircraft initiate deceleration maneuvers earlier in response to predicted air traffic on its course. In Figure 3 (b), 16 groups of bar

[2]Refer to this video clip for more details: `https://youtu.be/vS4Vo2mg9d8`

[3]At each simulation episode, a UAM aircraft flies to a single lane at a specific altitude, and 'minimum separation' refers to the closest point between aircraft and UAM over the episode duration. The figure illustrates the trend across all episodes, considering all altitudes and lanes.

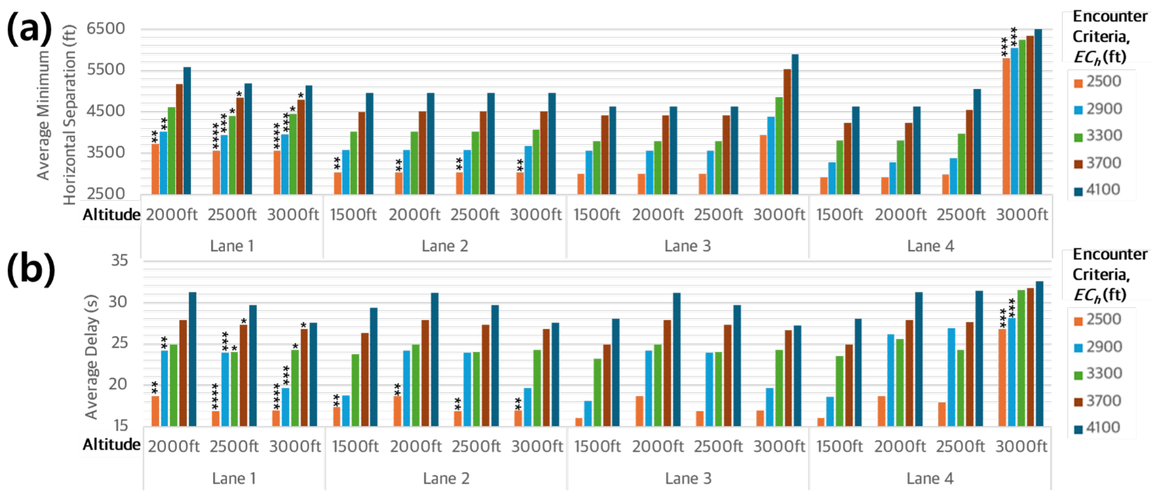

Figure 3 – *(a) average minimum horizontal separation and (b) average flight delay, for each lane and altitude under different encounter criteria*

charts show the average delays (*lower the better*) across lane and altitude combinations. In the case of (lane, altitude) = (3, 3000ft), the average delays are 17.0s, 19.7s, 24.3s, 26.7s, and 27.3s, for each EC_h, respectively, where reaching the waypoint takes 501s with no air traffic on its course. Generally, higher EC_h prompt UAM aircraft to decelerate earlier in response to predicted encounters, leading to increased delay.

The asterisks in Figure 3 represent instances of LoS during the two-day simulation. Lane 1 at 2500 ft and 3000 ft altitudes, along with Lane 4 at 3000 ft altitude, encounter curved trajectories of air traffic, necessitating higher EC_h to prevent LoS. Conversely, Lane 3 and the lower-altitude segment of Lane 4 encounter relatively linear air traffic trajectories, requiring lower EC_h for LoS prevention. The choice of the optimal lane and altitude combination depends on balancing efficiency and safety considerations. Lane 1 at 1500 ft altitude emerges as the safest option, experiencing no encounters but situated farthest from central Seoul. Lane 4 at 1500 ft altitude offers the most efficient option with lower delays and its proximity to central Seoul.

4 CONCLUSION

In conclusion, we introduced a framework for assessing the feasibility of UAM routes within terminal airspace, utilizing speed adjustments for UAM aircraft based on predicted distribution of trajectories of conventional aircraft. While our analysis focused on a specific area, the methodology can be applied to diverse regions with sufficient data inputs and with more refinement to account for distinct trajectory dynamics observed across various geographical contexts.

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