Dynamic Capacity Balancing in Urban Airspace: Comparing Historical and Real-time Aggregate Flow Data

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***Abstract*—As urban ground transportation congestion increases, there is growing interest in urban air transportation, such as delivery drones and air taxis. However, managing air traffic in densely populated urban areas poses significant challenges, which require effective flight planning, separation management, and airspace design. This paper investigates dynamic capacity balancing methods to manage air traffic in constrained urban airspace, where drones must fly above the existing road network. Specifically, it compares the effectiveness of labelling high-complexity zones using historical data versus real-time aggregate flow data. The results indicate that while both approaches reduce airspace intrusions and improve safety, the best approach depends on traffic demand levels. At lower demand levels, using historical data yields better safety outcomes, whereas using real-time data is more effective at higher demand levels due to its flexibility. At their best, both methods increase the travel distance by less than 6% while reducing airspace intrusions by 30% compared to a case without dynamic capacity balancing.**

***Keywords*—U-space, CD&R, tactical, dynamic, deconfliction, capacity, simulation, BlueSky**

I. Introduction

Ground transportation is becoming increasingly dense, particularly in cities like London, where people spend an average of 148 additional hours per year in traffic congestion [1]. This growing challenge has led to interest in employing delivery drones and air taxis to alleviate ground congestion [2]–[5]. In addition to reducing the time spent in traffic, urban air transportation could mitigate economic losses [6] and reduce emissions [7], [8].

However, anticipated densities in urban airspace far exceed those of traditional air traffic management [9]. At such high densities, flight planning, separation management, capacity management, and urban airspace design become interdependent. Therefore, an integrated approach is essential to enable safe urban operations [10]. Moreover, in some cities, tall buildings and critical infrastructure may constrain aircraft above the existing road network, further complicating flight operations [11]. This constrained airspace limits aircraft manoeuvrability and poses unique challenges for navigation.

In constrained airspace, aircraft cannot fly directly to their destinations and must follow a network. Coupled with non-uniform traffic demand, certain legs of the network may be more preferred than others, which can create hot-spots (zones of traffic convergence). Traffic convergence leads to increased traffic complexity [12], [13], which can decrease airspace safety. To address this, capacity balancing can be used to reduce local traffic and complexity in urban airspace.

Capacity balancing can be achieved centrally, with a single entity managing take-off delays [14] or dynamic airspace modifications [15]. However, such systems rely on operators to freely share operational data. Moreover, uncertainties such as wind and operational delay can complicate central planning. The ad hoc nature of urban missions further challenges advance planning [16]. As a result, we have previously developed decentralized dynamic capacity balancing concepts, allowing individual drones to adjust routes based on current airspace congestion [17], [18].

Our previous work on dynamic capacity balancing has utilized both real-time [17] and historical data [18] to aid in the creation of dynamic high-complexity zones so that aircraft may re-plan around them. The advantage of real-time data is that it provides current insight into airspace conditions. Conversely, historical traffic data offers a broader perspective on traffic patterns, which helps identify persistent congestion areas. This work aims to compare the performance of a dynamic capacity balancing method when relying solely on real-time data versus incorporating historical data to identify high-complexity zones. The work simulates air traffic above the city of Rotterdam under varying traffic demand levels.

Section II will explain the general capacity balancing system and explain the differences in using historical or real-time data for labelling high-complexity zones. Section III presents an experiment to compare the two methods for labelling high-complexity zones. Section IV will show the results of the experiment. Finally, Sections V and VI contain the Discussion and Conclusion, respectively.

II. Dynamic capacity balancing

Capacity balancing can be used to improve safety by reducing local traffic complexity and density in urban airspace. In this work, we perform capacity balancing by spreading traffic over the available airspace while attempting to limit the extra distance travelled (safety and efficiency trade-off). In this way, the local traffic density and complexity can be lowered dynamically. The overall process in which dynamic capacity balancing employed is as follows:

1) **Observation**: The safety events that have occurred in the past ten minutes in the airspace are gathered in the observation step. The safety events considered for the observations are unique conflict events (see Sec. Fig 1).
2) **High-complexity zone labelling**: Using conflict observations, the airspace is labelled into areas with high and

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low complexity. The areas of high-complexity airspace have an additional cost of travel.

3) **Replanning**: Aircraft use the updated cost of travel to decentrally create a new optimal route that considers the additional costs.

In this work, we consider two different methods for labelling high-complexity airspace. The first method additionally uses **historical data** to help label the airspace, while the second only uses the **real-time data** from the observation step. The historical method will use static and stable zones, while the real-time data will create dynamic zones that adapt to traffic fluctuations. Note that both methods will use real-time data to decide which airspace zones can be considered high-complexity.

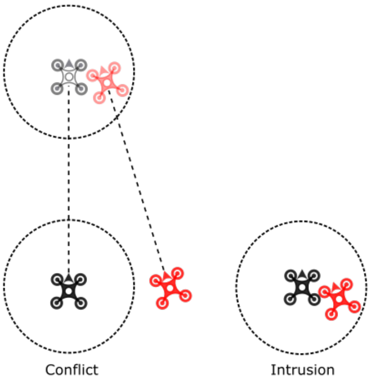


Figure 1. Conflict and intrusion diagram. An intrusion occurs when an aircraft enters the protected area of another aircraft (dashed circle). A conflict is counted when an aircraft is expected to become an intrusion within a lookahead time. It is up to the conflict resolution algorithm to solve conflicts before they become intrusions.

A. High-complexity labelling with historical data

Using historical traffic patterns for capacity balancing can identify general trends and locations prone to high complexity. By incorporating this historical perspective, we can remove fluctuations arising solely from real-time data, leading to more consistent labelling of high-complexity zones. Previous research has demonstrated that using historical data for capacity balancing can improve airspace safety [18]. We define historical data as the conflict locations derived from a scenario without any capacity balancing applied (see Sec. III-B). It is important to note that the historical data source in this work was developed from the same traffic demand distribution as the other scenarios within the experiment. However, in practical applications, capacity balancing methods would likely need to account for variable traffic demand patterns.

Once all conflict events from the historical scenario are collected, they are clustered using Ward's method [19]. Ward clustering is a variance-minimizing approach, similar to K-means, which takes a distance threshold for merging nearby clusters (90 meters). After clustering, we use the centroid of the clusters to create a Voronoi diagram. A Voronoi diagram creates polygons in which all points in a particular polygon are always closer to its centroid than any other centroid [20].

The resulting Voronoi diagram is illustrated in Fig. 2. Note that the shape and location of these zones remain constant throughout each scenario. During flight, every 10 seconds, the conflict-density of each Voronoi polygon is calculated by dividing the number of conflicts (within 10 minutes) by the total length of streets within that polygon. Subsequently, polygons with a conflict-density greater than zero are ranked based on their relative conflict-density. The top 75 percent of these polygons are then assigned an additional cost multiplier and are considered high-complexity zones. Any drone whose planned path traverses these high-complexity zones must recalculate a new path that takes this additional cost into account. The cost of travelling through a high-complexity zone is twice that of travelling through a low-complexity zone. The reason to choose 75 percent of clusters to receive the additional cost multiplier of two comes from the sensitivity analysis performed in [17].

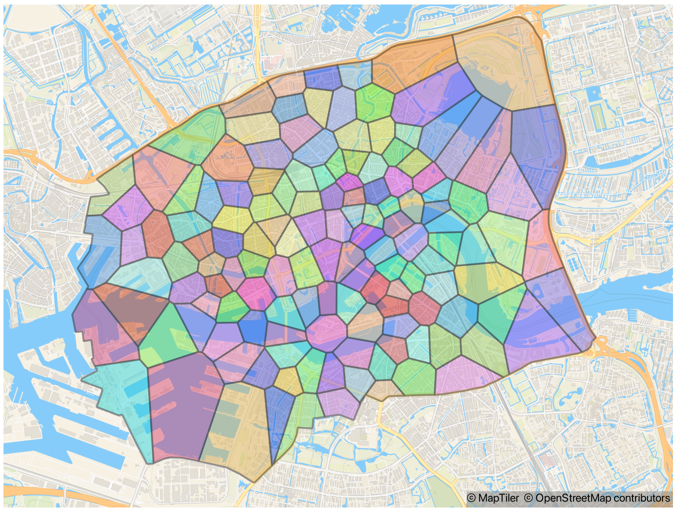


Figure 2. Static zones identified in Rotterdam airspace using historical conflict data. The location of these zones do not change. However, the zones labelled as high-complexity can change every 10 seconds.

B. High-complexity labelling with real-time data

Unlike labelling with historical data, using real-time conflict data for capacity balancing allows the aircraft to respond to the current condition of the airspace. This approach would be useful in mitigating situations that are not visible in the historical data timescale.

The method for high-complexity labelling with real-time data is derived from [17]. In this method, potential zones are not defined a priori: they are dynamic. Labelling the high-complexity zones only depends on the current observations. First, only the conflict events that have occurred within the last ten minutes (observations) are clustered with the Ward method. Then a convex hull polygon [21] is created which contains all members of the clusters.

Similarly to the historical data method, the conflict-density of the polygons is calculated and the top 75 percent of clusters receive the additional cost multiplier of two. An example of these dynamic high-complexity zones is seen in Fig. 3. Note that the size, location, shape, and label of the zones is changing every 10 seconds. All aircraft with a path that intersects these high-complexity zones must create a new optimal plan.

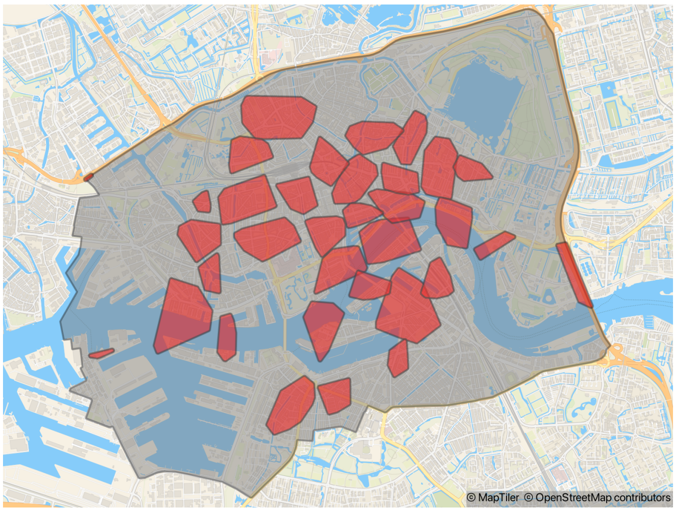


Figure 3. Dynamic zones identified in Rotterdam airspace using real-time conflict data. Note that the image shows the high-complexity zones at one specific moment in time. The amount, size, shape, and locations of these zones can change every 10 seconds.

III. Experiment

The experiment will compare using historical versus real-time data to label the high-complexity zones of a dynamic capacity balancing system. It will also present a baseline case that does not perform any dynamic capacity balancing.

A. Common Elements

1) Urban Airspace

The urban airspace used in this work is the city of Rotterdam (Fig. 4). The street network was downloaded from OpenStreetMap using the OSMNX python package [22], [23]. After downloading, the street network is processed so that roundabouts and parallel streets are simplified. Moreover, virtual 'bridges' were added to provide additional crossing points over the waterways of Rotterdam.

Previous research has shown that a one-way network for urban airspace is safer than a two-way network [24]. Therefore, a one-way network is designed to ensure that all intersections are reachable. The first step is to group continuous streets into groups using the COINS algorithm [25]. In the second step, a genetic algorithm is used to determine the directionality of the groups. More information about the urban airspace set-up can be found in [11] and [17].

2) Aircraft missions

The MASS-GT [26], [27] project made an estimate of the neighbourhood parcel demand in the city of Rotterdam. Fig. 5 shows the relative demand of the neighbourhoods in the Rotterdam airspace seen from Fig. 4. This demand is used to create the traffic distribution considering the take-off locations and destinations.

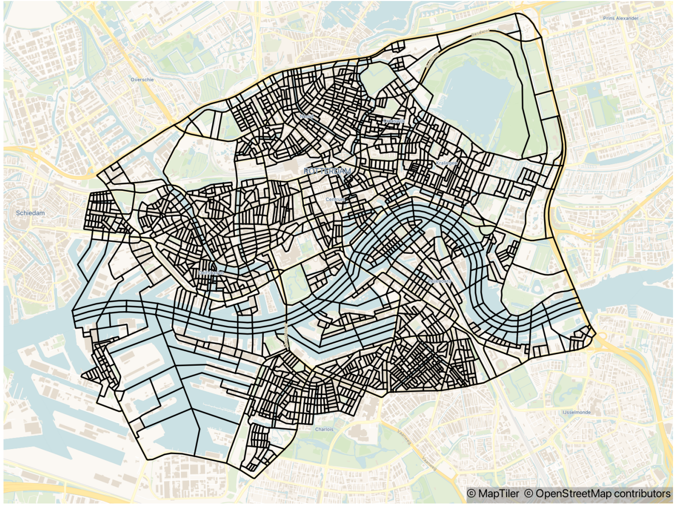


Figure 4. The constrained airspace in Rotterdam (Area= 50 km^2).

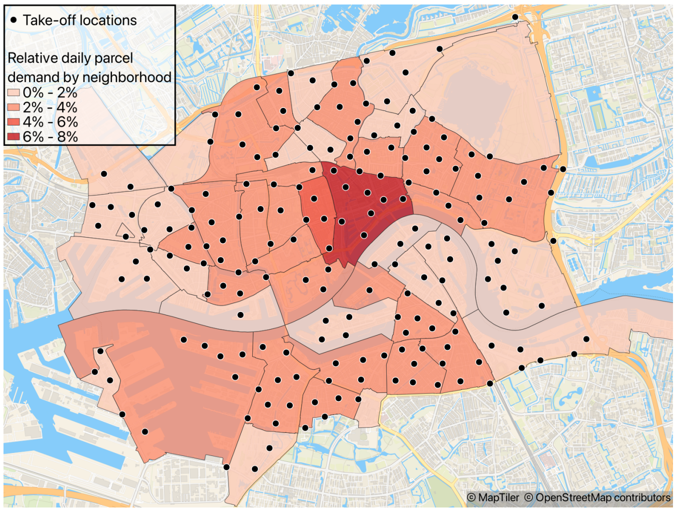


Figure 5. Take off locations and relative parcel demands by neighbourhood. The relative parcel demand is from the MASS-GT project [26], [27].

The take-off locations for all potential missions are also shown in Fig. 5. They are placed at least 300 metres from each other and are ensured to be outside of water bodies. The destinations are all other nodes in the street network that are outside of water bodies. Each mission starts by randomly selecting one of the take-off locations. The destination is chosen by considering the weighted probabilities and by ensuring that the mission is at least 1000 metres long. The plan is created by finding the shortest path between the two nodes considering the length with the Dijkstra algorithm [28]. All missions take place at 30 feet above ground.

3) Replanning module

Aircraft that intersect any high-complexity zone in their future path must search for a new optimal plan. Since a new observation is made every ten seconds, aircraft continuously check for lower cost plans. The new plans are created by finding the shortest path between the current position and the destination with the Dijkstra algorithm. The streets in high-complexity zones receive a cost multiplier of 2.

4) Conflict detection and resolution

This work uses state-based conflict detection. This method linearly extrapolates the current position of all aircraft with a given look-ahead time and checks whether they will violate the protected zone (Fig. **??**). The drones use a tactical speed-based conflict resolution algorithm from [29] to solve conflicts before they become intrusions. The method relies on a horizontal protected radius of 32 metres (Table 3.7.2.4-1) [30] and a 10 second look-ahead time. Note that a limitation of state-based conflict detection in constrained airspace is that it detects a large amount of false conflicts [11]. However, these false conflicts provide information where aircraft are near each other, so they are also taken into account for this work.

5) Aircraft model

All aircraft in this work are modelled after a Matrice 600 pro drone with performance parameters described in Table I.

TABLE I. DJI MATRICE 600 PRO DRONE PERFORMANCE PARAMETERS [31].

Parameter	Value
Max. horizontal speed	12.9 m/s
Avg. horizontal speed	10.3 m/s
Min. horizontal speed	0 m/s
Max. take-off mass	15 kg
Acceleration/Deceleration	3.5 m/s^2

6) Simulation software

This work used the BlueSky air traffic simulator for the experiments [32]. BlueSky is a fast-time simulator that can be extended via plugins so that different methods of labelling high-complexity zones can be compared.

B. Independent variables

The independent variables of the experiment are as follows

- Aggregate flow data labelling: Baseline (no capacity balancing), Historical data, Real-time data.
- Imposed traffic demand level: 100, 200, 300, 400, 500 simultaneous aircraft in the air. These correspond to densities of 2, 4, 6, 8, 10 $drones/km^2$, respectively. The low value is similar to what was estimated in [9], while the high value is about 2 times the highest density in [9].

Each case is repeated 5 times with a different random seed that generate different origin-destination pairs. This creates 3 (data methods + baseline) x 5 (traffic demand levels) x 5 (randomly selected random seeds) = 75 different scenarios. Each scenario simulates aircraft missions for 2 simulation hours.

The historical data scenario was created with 300 aircraft with the demand distribution in Fig. 5. Capacity balancing is not employed (baseline) in the historical scenario and a different random seed is used to select the origins and destinations. The conflict events of the historical scenario created the zones shown in Fig. 2.

C. Dependent measures

This work will use three different dependent measure categories. These are **Safety**, **Efficiency**, and **Airspace**.

1) Safety

We consider conflicts and intrusions as the relevant safety metrics. However, these are not presented in absolute terms. First, the conflicts and intrusions are scaled by the total number of flights. This gives the number of conflicts and intrusions per flight.

We also present the safety metrics scaled with the distance travelled as a percentage of the baseline case. The metrics are conflicts and intrusions per distance percentage. For example, assume the results show that using real-time or historical data yields 105 intrusions per distance percentage. This means that on average, aircraft encountered 5 percent more intrusions per distance when compared to the baseline. Conflict/intrusions per distance are useful metrics for this experiment because an aircraft with an initial identical route may fly a different route depending on the data labelling method.

2) Efficiency

Efficiency metrics are related to how much distance aircraft fly. As the flight distance increases, the efficiency of the flight decreases. For this category, two metrics are observed.

First, the horizontal distance travelled as a percentage of the baseline case is shown. Assuming that one concept shows a distance percentage of 105 percent, it would mean that, on average, aircraft flew 5 percent more distance as compared to the baseline case without dynamic traffic management.

Second, the number of replans per flight is shown. The number of replans per flight will indicate how many times aircraft are changing their original plan. A value equal to one would show that all aircraft make on average one new plan during flight. Note that this metric is not shown for the baseline case because they do not perform any replans.

3) Airspace

There is an observation of the airspace made every 10 seconds to find the high-complexity zones. This means that the amount and location of airspace labelled as high-complexity can vary throughout the simulation. Therefore, two metrics related to the airspace are presented.

The first metric measures on average the percentage of airspace that is labelled as high-complexity. The second metric measures the temporal stability of high-complexity airspace. This represents the average percentage overlap of the clusters from one observation to the next. A value of 100 percent would indicate that the high-complexity airspace is completely identical from one observation time step to the other.

IV. RESULTS

The following section presents the results of the simulations. Unless otherwise noted, all figures show the imposed traffic demand level on the horizontal axis and the dependent variable in the vertical axis.

A. Safety

Figs. 6a and 6b shows the number of conflicts and intrusions per flight, respectively. Both plots show similar trends. All three concepts, baseline, historical data, and real-time data, show an upward trend in conflicts and intrusions per flight as the traffic demand increases. However, it is clear that the dynamic capacity management concepts perform better than the baseline concept. Moreover, it is seen that using real-time data for dynamic capacity management is better than historical data, especially at the higher demand levels.

Figs.6c and 6d show the conflicts and intrusions per distance as a percentage of the baseline, respectively. The dashed horizontal line represents the baseline concept. Regarding the conflicts, both the historical and real-time data concepts show little improvement over the baseline at a traffic density of 100 simultaneous aircraft. However, they both decrease to about 85 percent of the baseline at the higher demand levels, with the real-time data concept showing a slightly lower number of conflicts per distance travelled. The intrusions per distance percentage is similar but exhibits some important differences. First, at 100 aircraft in the air, it is clear that using historical data reduces the intrusions per distance to an average of 71 percent of the baseline. Meanwhile, at the same demand level, using real-time data does not show an improvement. As the demand level increases, using historical data keeps the intrusions per distance percentage constant. However, at 300 and 400 aircraft in the air, using real-time data for dynamic capacity management show a 10 percent improvement over using historical data. At 500 aircraft in the air, using real-time data for dynamic capacity management is not as efficient as lowering the intrusions per distance percentage, as with 300 and 400 aircraft.

B. Efficiency

Fig. 7a shows the distance travelled as a percentage of the baseline concept without any dynamic capacity management. As expected, using historical and real-time data for dynamic capacity management increases the overall distance travelled. The figure also shows that as the demand level increases, the additional distance travelled also decreases when using historical and real-time data. However, it is clear that considering historical data does not increase the extra distance travelled as much as when using real-time data.

Fig. 7b shows the number of re-plans per flight. This shows a similar trend to Fig. 7a, which is that re-plans per flight tend to decrease with increasing demand level. Moreover, considering historical data for dynamic traffic management tends to reduce the number of re-plans per flight as when using real-time data.

C. Airspace

Fig. 8a shows the percentage of airspace that is considered high density. Using historical data for dynamic capacity management tended to label more high density compared to using real-time data. Both concepts increase the percent of high-complexity airspace with increasing demand level. However, the increase is faster at the lower demand levels and then tapers at higher demand levels. With historical data, a maximum of 60 percent of the airspace is labelled as high-complexity, while with real-time it is less than 50 percent.

Fig. 8b shows the high-complexity temporal stability. Note that it measures how stable the locations of high-complexity are, an average between observations steps. A value of 100 percent indicates that high-complexity airspace does not change between observation steps. The figure exhibits that using historical data creates very stable high-complexity zones that are on average 90 percent the same from one density observation to the next step. Using real-time data for dynamic traffic management tends to have lower high-complexity stability than when using historical data. It increases from around 65 percent at lower demand levels to around 70 percent.

V. Discussion

A. Safety

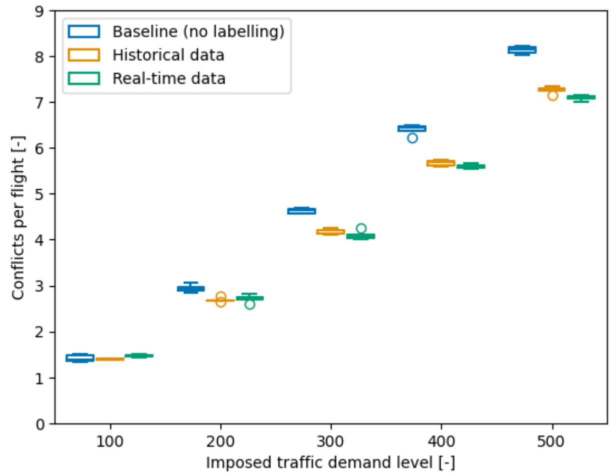
Interestingly, the results showed that the strategy used to label high-complexity zones changes the effectiveness of the dynamic capacity balancing method at different demand levels. When the demand level is low (100 aircraft), using historical data was able to reduce the conflicts per distance to about 70 percent of the baseline. Meanwhile, real-time data is not as effective. This is because the historical data method is able to identify the shape of the zones that are high-complexity. This means that the stability provided by historical data is beneficial when there is not enough real-time data to create useful high-complexity zones.

However, as the airspace becomes increasingly dense, using real-time data begins to yield better results. This means that there is enough information so that the dynamic capacity balancing system can effectively reduce the number of intrusion events. Using real-time data also starts to outperform using historical data. This again shows that using historical data can help increase safety when there is not enough information in the airspace. However, with increasing density, the flexibility allowed with real-time information becomes more important in finding and avoiding high-complexity airspace.

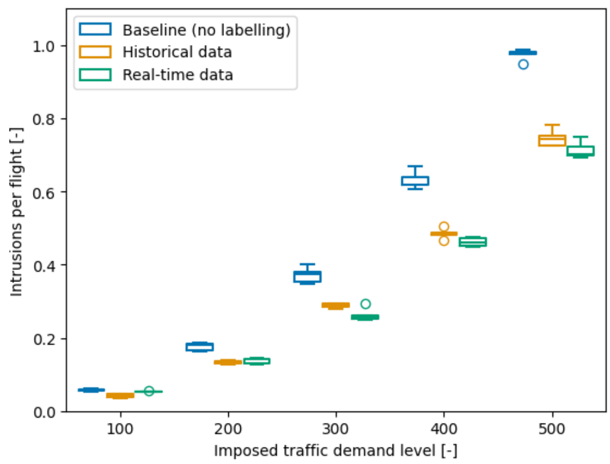
Moreover, using real-time information tends to show constant relative improvement over the baseline in terms of intrusions. Using real-time information reaches its maximum improvement over the baseline at around 400 aircraft, and then starts to decrease in effectiveness at the highest demand level. At very high densities, there is more of a chance of encountering false conflicts. False conflicts are typically encountered in constrained airspace, when using state-based conflict detection. Due to the orientation of the street, a detected conflict may never actually become an intrusion.

B. Efficiency

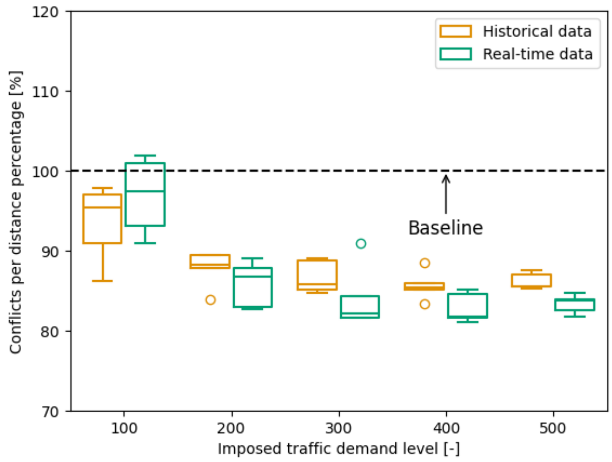
Both high-complexity labelling concepts increase the extra distance travelled as compared to the baseline by less than 10 percent, and the difference between both is quite small. However, it is clear that as the traffic demand level increases, the aircraft travel less additional distance. Due to



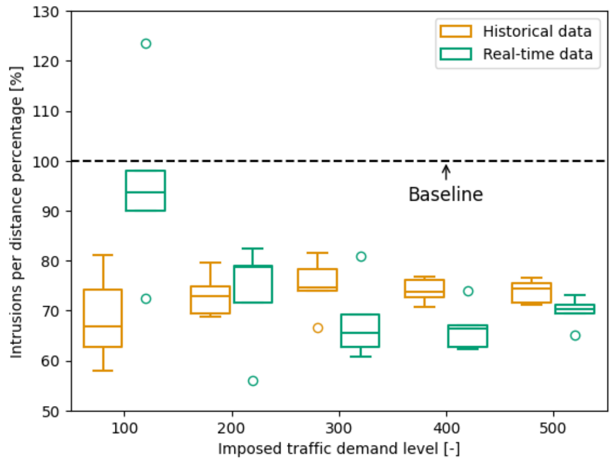
(a) Conflicts per flight.



(b) Intrusions per flight.

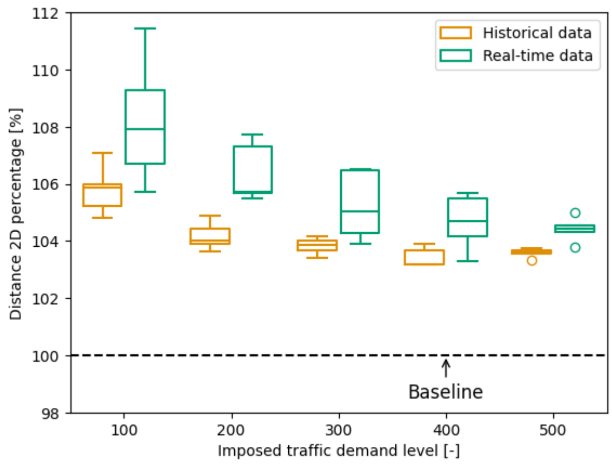


(c) Conflicts per distance percentage, where the baseline represents 100 percent.

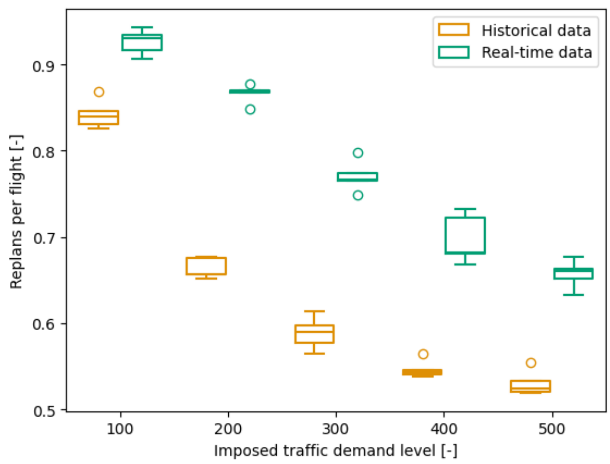


(d) Intrusions per distance percentage, where the baseline represents 100 percent.

Figure 6. Safety: These plot show the conflicts and intrusions per flight in Fig. 6a and Fig. 6b, respectively. It also shows the conflicts and intrusions per distance percentage in Fig. 6c and Fig. 6d, respectively.

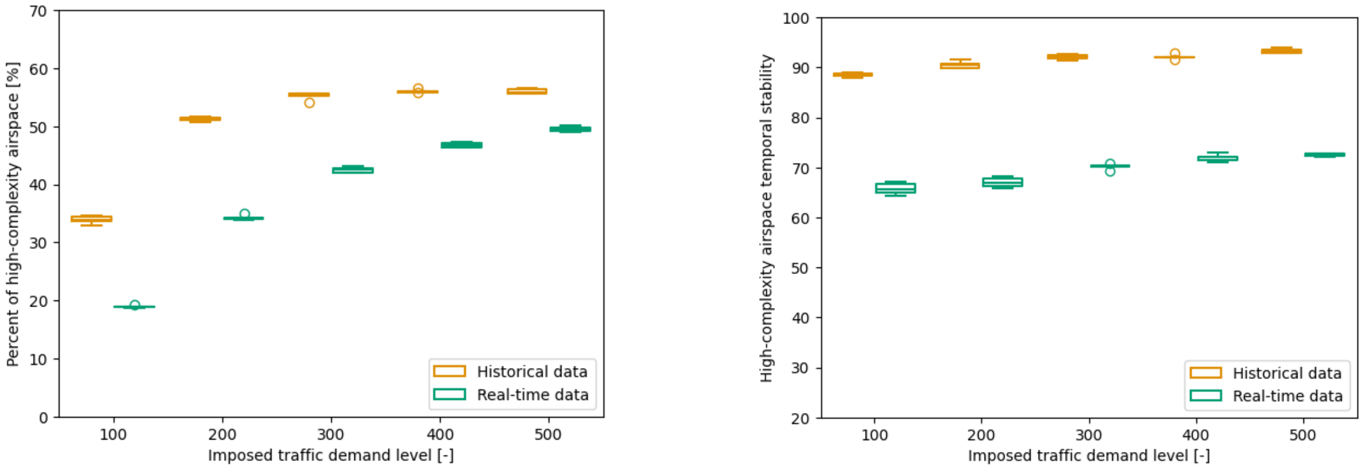


(a) Distance as percentage of the baseline case.



(b) Replans per flight.

Figure 7. Efficiency: These plots show the distance percentage and amount of replans per flight in Fig. 7a and Fig. 7b, respectively.



(a) Percent of high-complexity airspace.

(b) High-complexity temporal stability.

Figure 8. Airspace: These plots show the percent of high-complexity airspace and high-complexity temporal stability in Fig. 8a and Fig. 8b, respectively.

the increased conflicts observed in the airspace, the amount of high-complexity zone airspace increases. This makes it difficult to plan around, so there are fewer re-plans per flight. Interestingly, it also means that not all aircraft need to replan to see a beneficial effect in safety.

It can be seen that using historical data for dynamic capacity balancing makes aircraft more predictable, since they tend to perform fewer re-plans and travel less distance. However, this predictability is more useful at low demand levels when the airspace does not provide enough information to make real-time data useful. At higher demand levels, more replans per flight allow the real-time data zones to better distribute traffic.

C. Airspace

It is also seen that about 30 percent of the airspace should be high-complexity in order to see the beneficial effects in terms of intrusions. At the lowest demand level, using historical data makes 30 percent of the airspace classified as high-complexity. This is around 20 percent for when using real-time data. However, when the real-time data is at 30 percent at 200 aircraft, a relative improvement in the number of intrusions matches that of historical data. Moreover, at the higher demand levels, too much of the airspace is high-complexity as compared to real-time data, which allows the real-time data more flexibility in isolating the high-complexity zones and therefore spreading traffic better.

The airspace results also illustrate the reason why the distance travelled and number of replans per flight decrease with increasing traffic demand level for both concepts. As more of the airspace is labelled as high-complexity, more aircraft are not able to find an alternative route that decreases the overall cost of travel. Therefore, they perform less replans which means the extra distance travelled tends to decrease with density.

The predictability of using historical data is again seen in the high-complexity temporal stability. On average, about 90 percent of the airspace labelled as high density is the same from one observation time step to the next when using historical data. The predictability of the real-time data high-complexity zones only reaches a maximum of around 70 percent.

VI. Conclusion

The aim of the study was to study the differences between using historical and real-time conflict data to create areas high-complexity with dynamic capacity balancing. The results show that a decentralised dynamic capacity balancing method always shows improvement in terms of intrusion events at low and high demand levels. However, at lower demand levels, the dynamic capacity balancing method performs better in terms of safety if it uses historical data to label high-complexity zones because it used past information to generate the likely problematic zones.

As the traffic demand level increases, it is better for safety to use real-time data to identify high-complexity zones. The increased flexibility with real-time data means the high-complexity areas can be identified and aircraft can plan around them. Nevertheless, both data labelling methods increase the extra distance travelled by less than 6 percent while reducing the observed intrusions to around 70 percent of a case without dynamic capacity balancing. In practice, a dynamic capacity balancing should make use of both real-time and historical data. Therefore, future research should study how best to combine the benefits of both data sources.

Moreover, the historical data in this work was derived from a similar demand distribution than what was experienced in the experimental scenarios. In reality, the demand distribution can vary. Therefore, more research should be made that considers the demand distribution variation between the historical data and the actual missions, especially at low demand levels, since depending on real-time data is least effective there.

Also, both data labelling methods have a reactive nature. There need to be conflicts in the airspace so that zones can be labelled as high-complexity. This is the decentralised nature of the dynamic capacity balancing method. Therefore, research into combining this system with a more strategic approach could be beneficial.

Additionally, there are a number of limitations in the general dynamic capacity balancing method itself that require further study. Although [17] studied the effect of modifying the percentage of clusters with an additional cost-multiplier, it was still one dimensional. A more granular approach that adapts this percentage based on local density or complexity could yield better results. Similarly, other factors of the method (the 10-second update rate and the 10-minute data gathering) should be studied further. Future research should focus on how this balancing method fits within the broader U-Space framework.

DATASET AND SOFTWARE AVAILABILITY

The source code and results of the concepts presented in this work are openly available online [33].

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