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Area Navigation Terminal Airspace Complexity Estimation for Arrivals

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***Abstract*—Modern navigation systems such as Area Navigation (RNAV) yield new challenges for developing data-driven algorithms and new perspectives in defining the safety and complexity of the terminal airspace due to the complicated maneuvers of aircraft. In this paper, we propose a complexity estimation framework for RNAV terminal airspace. The framework integrates our previously developed algorithms for trajectory pattern identification, multi-agent trajectory prediction, and Gaussian mixture model-based anomaly detection. All algorithms are developed to be implemented in the complex situation of RNAV terminal airspace. The estimated complexity prompts researchers and air traffic controllers to investigate situations where the complexity is abnormally high for potential risks or operational errors. The proposed complexity estimation framework is tested with real air traffic surveillance data recorded in Incheon International Airport, South Korea.**

***Keywords*—airspace complexity, area navigation, trajectory clustering, anomaly detection, trajectory prediction**

I. INTRODUCTION

Continuous growth in the demand of air traffic has made the terminal airspace more crowded and complex than ever, with an average growth rate of 2.6 percent for the next 20 years forecast by the Federal Aviation Administration (FAA) [1]. In response to such growth, Air Traffic Controllers (ATCs) have to direct the air traffic flow more frequently, resulting in potential safety hazards. Therefore, it is important to accurately estimate the complexity of the airspace.

Airspace complexity has been an area of interest for many years and extensive research has been conducted in the past two decades. One of the first works is done by NASA in [2–5]. In those works, the concept of dynamic density and complexity factors that mainly focus on the number of aircraft in a sector and other characteristics such as the relative position between aircraft are proposed. Extensive experiments and efforts have been done to review the accuracy of the computed complexity. In [6], Kopardekar and Magyarits first collect subject-matter experts' ratings of the complexity, and then compare how well the different dynamic density metrics fit to the ratings by using a linear regression method. The authors find that a unified metric with complexity factors from different literature performs the best, and the dynamic density performs better than the simple aircraft count, which was the basis of the complexity measure at that time. Besides using complexity factors, topological methods are also used to evaluate airspace complexity. Delahaye et al. model the set of aircraft trajectories by a linear dynamical system and compute the Kolmogorov entropy as the complexity [7]. The authors later extend the algorithm by using a non-linear dynamical system and add the time dimension in order to compute the complexity in a 4-dimensional space [8]. In addition, as big data analysis becomes popular, data with complexity levels labeled by subject matter experts are built, allowing researchers to use machine learning techniques to discover complexity factors from the labeled data. Andrasi et al. use a feedfoward neural network to find the correlation between complexity factors and the subjective complexity scores [9], and Cao et al. use deep learning to train a classifier that can categorize the air traffic data based on low, normal, and high complexity [10].

The above mentioned works all focus on the complexity in the en-route airspace. However, terminal airspace is the most complex part of the airspace and where most fatal accidents happen [11]. Therefore, Netjasov et. al proposed a metric for measuring complexity of traffic in a given terminal airspace [12, 13]. In those works, the terminal airspace complexity is divided into static complexity and dynamic complexity. The static complexity accounts for the complexity from the airspace structure such as standard terminal arrival routes and the dynamic complexity accounts for the complexity from the interactions between aircraft such as conflicts. Now with the emergence of new navigation systems such as Area Navigation (RNAV), aircraft have more freedoms and ATCs tend to give more vectoring commands for more efficient sequencing and scheduling. Although vectoring commands improve the airspace efficiency, they can make the airspace much more complex. Since previous works focus on the en-route airspace or typical terminal airspace, which do not have as complicated maneuvers and traffic volume and situation as the RNAV terminal airspace, a new RNAV terminal airspace complexity metric is needed. The most recent effort in this is done by Gariel et al. where vectoring flights are considered for the first time and the complexity is computed as the entropy contributed by abnormal flights in the airspace [14]. However, as we deepen our research in various fields such as trajectory pattern identification and anomaly detection, we realize the abnormal flights classified in [14] can be much more refined in the RNAV terminal airspace. For example, in airports where RNAV is widely adopted, various vectoring patterns, trajectory patterns that deviate from the procedures, are generated. There may be vectoring patterns that deviate from the procedures so much that they seem to be abnormal but actually normal in terms of the daily operation in the airspace [15]. In addition, energy-related anomalies have been proposed to be critical to safety [16], and with the existence of complex vectoring patterns, detecting energy-related anomalies becomes more tricky [17]. Thus, the complexity estimation cannot reflect the true complexity and workloads that ATCs perceive unless the special traffic situation in the RNAV terminal airspace is taken into account. Without a faithful estimation of the complexity, ATCs' workload and some algorithms' performance such as 4D trajectory optimization are difficult to be quantified and compared. Operational and more potential anomalies can also be overlooked. Therefore, this paper proposes a new RNAV terminal airspace complexity estimation framework. The framework not only includes typical abnormal flights such as go-arounds and holding flights, but also abnormal flights in vectoring patterns, interactions between aircraft, and energy-related features. Each part utilizes our previously developed algorithms, i.e., trajectory pattern identification and classification [15], multi-agent trajectory prediction [18], and Gaussian mixture model-based anomaly detection [17], respectively.

The rest of the paper is organized as followed: Section II describes the data being used to test the proposed complexity estimation framework. Section III presents and explains each component in the framework. The test results are presented in Section IV, and conclusion is given in Section V.

II. Data Description and Preparation

The data being used to test the proposed complexity estimation framework is the Automatic Dependent Surveillance-Broadcast (ADS-B) data recorded in the Incheon International Airport (ICN) in South Korea, and Aeronautical Information Publication (AIP) data. The ADS-B data contain the aircraft's states (longitude, latitude, altitude, ground speed, vertical speed, and course angle) as well as time and the flight information. The AIP data provide important information about an airport's operations, regulations, and routes. One of the uniqueness of ICN is that it widely uses Area Navigation (RNAV) for its arrival procedures. In fact, there are in total 14 RNAV Standard Terminal Arrival Routes (STARs) in ICN, shown as black lines in Figure 1, while only 1 RNAV STAR is used in the John F. Kennedy International Airport [17]. Each triangle marker in the black lines represents a fix in that STAR. The four red markers represent the four entry fixes which are where the flights enter the ICN terminal airspace. After entering the airspace, the flights travel to one of the Initial Approach Fixes (IAFs), the green markers in Figure 1, and enter the approach phase where the fixes are represented by the black circles. The flights then enter the landing phase when they reach one of the Final Approach Fixes (FAFs), the yellow markers in Figure 1. For data preparation, we preprocess the ADS-B data by cutting the

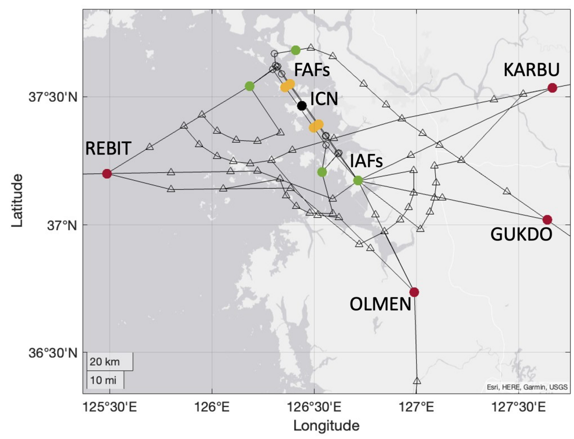

Figure 1: STARs, FAFs, and IAFs in ICN

flights from 70 nm away from the airport to the FAFs because 70 nm is roughly where the flights are just before they enter the terminal airspace and the FAFs are where they enter the landing phase. When the traffic is light, Air Traffic Controllers (ATCs) often give flights direct-to commands, in which case the flights directly go to the farther fix by skipping fixes in between. However, when the traffic is heavy, ATCs often give vectoring commands that deviate flights from the STARs. Figure 2 shows an example of a vectored flight. It can be seen that the flight follows the STARs after it enters from OLMEN, but then deviates to the West where there is no STAR related to OLMEN at all. Although that flight may seems to be abnormal, it is actually common in the operation of ICN for maintaining the sequencing and scheduling under high traffic volume. To further illustrate this, Figure 3 shows

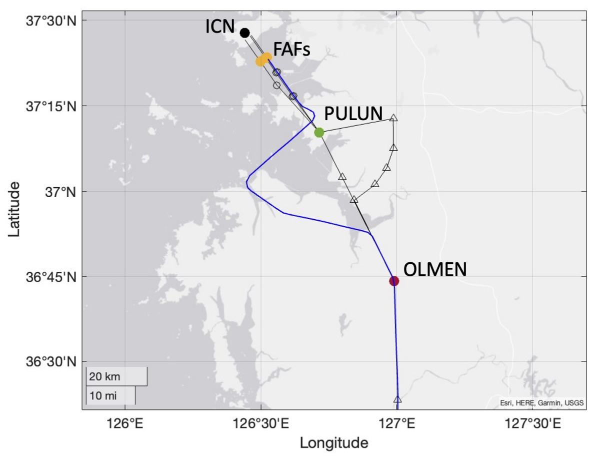

Figure 2: A vectored flight

all arrivals on May 23 where almost every flight deviates from the STAR. Therefore, ICN's RNAV terminal airspace is very complex and when estimating the airspace complexity, such vectoring must be taken into account and cannot be simply treated as abnormality.

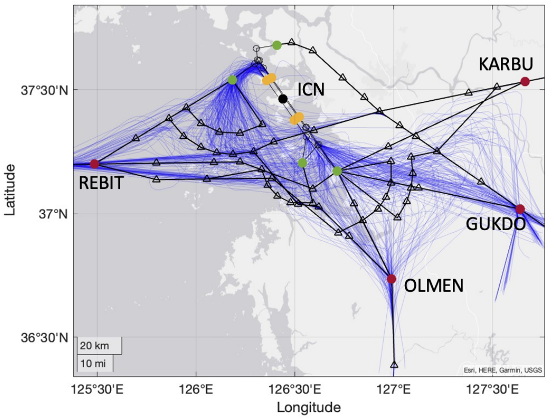

Figure 3: All arrivals on May 23

III. Methodology

The proposed complexity estimation framework is shown in Figure 4. The complexity estimation is a linear combination of each component in the framework.

$$C = \alpha_v C_v + \alpha_s C_s + \alpha_a C_a \tag{1}$$

The parameters, α_v, α_s, and α_a, are each component's coefficient. In this study, we treat each coefficient as equal. However, it may be adjusted based on human expert feedback or computed by linear regression with labeled complexity measure from human experiments. Each part implements our previously developed algorithms and the framework integrates them in a careful manner to accurately estimate the RNAV terminal airspace complexity. The following subsections explain individual components in the framework and how are they combined to estimate the complexity.

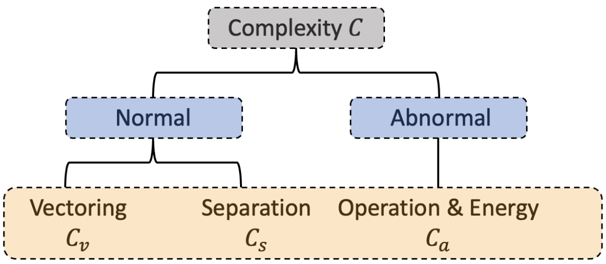

Figure 4: Proposed complexity estimation framework

A. Vectoring complexity

Vectoring is common in the RNAV terminal airspace such as ICN, but although vectoring looks random, there actually exist some common behaviors which form vectoring patterns. Unlike regular trajectory patterns, or clusters, vectoring patterns are more overlapped, and thus much harder to be identified. In [15], we propose a trajectory pattern identification and classification framework that can clearly identify various vectoring patterns and classify a flight into one of them in real time. The framework first utilizes the Dynamic Time Warping (DTW) to measure the dissimilarities between flights and constructs a dissimilarity matrix. The dissimilarity matrix is then used for the hierarchical clustering where a certain number of clusters (vectoring patterns) is selected based on the criteria, i.e., whether or not most flights in the clusters follow the same set of fixes. By using the trajectory pattern identification framework, complicated vectoring patterns in an RNAV terminal airspace can be clearly identified. Figure 5 shows the centroid of the identified vectoring patterns formed by all flights that enter from the OLMEN entry fix in ICN. As discussed in [15], the trajectory

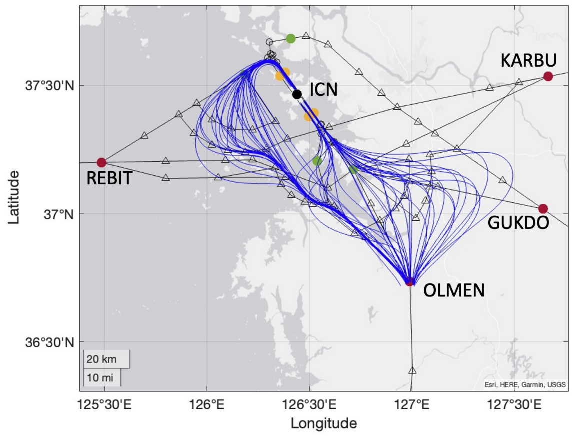

Figure 5: All vectoring pattern centroids for OLMEN

pattern identification framework inevitably produces some trajectories that do not belong to any vectoring pattern due to their uncommon behaviors. Therefore, they contribute to the total complexity in the airspace while other trajectories are treated as normal operations and do not contribute to the total complexity. In this paper, the vectoring complexity is calculated using the referenced vectoring pattern centroid that is closest to the unusually vectored flight, determined through DTW. Consider a flight $X^f \in \mathbb{R}^{T_f \times N}$ and the referenced pattern centroid $X^r \in \mathbb{R}^{T_d \times N}$ where T_f, T_d, and N are the total number of time steps of the flight, the total number of time steps of the referenced pattern centroid, and the number of features, respectively. Note that all centroids are resampled into a fixed number of steps but each flight has its own total flight time. Thus, to compute their distance, the DTW is used [19]. In general, DTW finds a warping function that connects every pair of data points in the two time-series sequences that delivers the minimal distance, which minimizes the time discrepancies between them. Given a time period that starts at T_{start} and ends at T_{end}, C_v in every time step $t \in [T_{start}, T_{end}]$ is defined as:

$$\begin{aligned} C_v^t &= \sum_{i=1}^{M_v^t} \sum_{j=t^f_{start}}^{t^f} \sqrt{(X_j^{f_{i,hori}} - X_{dtw_j}^{r_{i,hori}})^2} \\ t^f_{start} &= \begin{cases} t^f - \Delta t, & \text{if } t^f > \Delta t \\ 1, & \text{otherwise} \end{cases} \end{aligned} \tag{2}$$

where t^f is the time step in X^f that is matched to t, and thus t^f_{start} is t^f minus a time window Δt, which is 2 minutes in this paper. $X_j^{f_i,hori}$ is the longitude and latitude in the ith flight X^{f_i} at time step j, and $X_{dtw_j}^{r_i,hori}$ is the longitude and latitude at the time step dtw_j in X^{r_i}, which is paired to the time step j in X^{f_i} by the warping function from DTW. Note that only the horizontal plane is considered in this paper because when ATCs make vectoring commands, they mainly focus on vectoring on the horizontal plane due to the flight level restrictions. M_i^t is the total number of flights in the airspace at time step t that are unusually vectored, so X^{f_i} is the i^{th} flight and X^{r_i} is the referenced pattern centroid corresponding to that flight. If multiple time steps are paired to time step j, the step that delivers the minimal distance is chosen. In general, C_v^t is an accumulated distance to the referenced centroid within a time window, which is to make sure the unusually vectored flight does not contribute to the complexity during its entire flight. We find that this is more realistic since the unusually vectored flight barely contributes to the complexity after it returns to one of the vectoring patterns, e.g., during its approach phase. C_v is normalized between 0 and 1 when it is used to compute the total complexity C for the ease of interpretation and comparison to other components.

B. Separation complexity

ATCs usually go through a situational awareness process in their minds before executing any decisions [20] and the separation between aircraft has been proven to be important in the reviewed literatures in Section I. Thus, the trajectory in the future can represent the complexity and ATCs' workload. To obtain the predicted separation, we use the multi-agent trajectory prediction framework that we proposed in [18]. The framework implements a sequence-to-sequence Transformer-based structure and is trained scenarios by scenarios. In the framework, the agent-aware attention [21] is used to help the neural network pay attention to other agents (flights) in the airspace so that the traffic situation is taken into account. We modify the framework so that it generates a 2-minute prediction every time step with the information in the last 2 minutes. The prediction is made for every arrival flight in the airspace. An example is shown in Figure 6. The prediction starts at the blue circle located at the end of every blue line, which is the input of the trajectory prediction framework. The blue tail from each blue circle is the position of the flight in the last 2 minutes. The red points are the 2-minute predictions. The separation complexity at every time step $t \in [T_{start}, T_{end}]$ is defined as:

$$
\begin{aligned}
C_s^t &= C_{s_{hori}}^t + C_{s_{vert}}^t \\
C_{s_{hori}}^t &= \begin{cases} -\dfrac{min(X_{pred}^{t,hori})}{s_{hori}} + 1, & \text{if } min(X_{pred}^{t,hori}) \\ & \leq s_{hori} \\ 0, & \text{otherwise} \end{cases} \qquad (3) \\
C_{s_{vert}}^t &= \begin{cases} -\dfrac{min(X_{pred}^{t,vert})}{s_{vert}} + 1, & \text{if } min(X_{pred}^{t,vert}) \\ & \leq s_{vert} \\ 0, & \text{otherwise} \end{cases}
\end{aligned}
$$

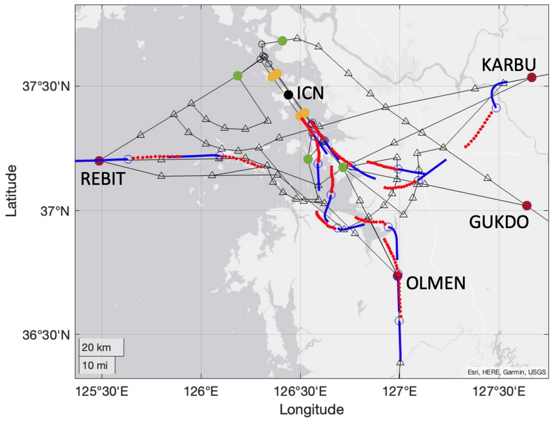

Figure 6: An example of the multi-agent trajectory prediction

where $X_{pred}^{t,hori}$ and $X_{pred}^{t,vert}$ are the absolute value of the predicted horizontal and vertical separation distance between all flights in the airspace except themselves, at time t. s_{hori} and s_{vert} are set to be as 5 nm and 1000 ft, respectively, based on the separation rule in the terminal airspace [22]. Equation (3) is designed in a way that $C_{s_{hori}}^t$ and $C_{s_{vert}}^t$ increase linearly from 0 to 1 when the separation is less than the minimum requirement. Similar to the vectoring complexity C_v, the separation complexity C_s is normalized between 0 and 1.

C. Anomaly complexity

Although anomalies may not always lead to unsafe events, they have large potentials to cause significant operational safety risks [23]. Therefore, anomalies need to be considered for estimating the complexity. Anomalies in the RNAV terminal airspace are different and more difficult to define and detect than those in en-route or other terminal airspace. To be more specific, anomalies need to be defined based on the vectoring patterns and traffic situation. In [17], we proposed an online anomaly detection framework. The anomaly detection framework is based on the Gaussian Mixture Model (GMM), which uses a weighted sum of the probability density functions of Gaussian components to best fit the training data distribution [24]. The number of Gaussian components is selected using sensitivity analysis with the Bayesian information criterion [25]. Each Gaussian component represents a vectoring pattern, and anomalies are detected by the Z score of each feature of the flight. The Z score is a widely used statistical measure for anomaly detection [26, 27]. When the Z score of a certain feature is greater than 2, this flight is anomalous in that feature [17]. Since energy management is tightly related to safety [16], anomalies in energy-related features are considered in this paper, i.e., ground speed, Specific Potential Energy Rate (SPER), and Specific Total Energy (STE). SPER and STE are derived from the ADS-B data by using the equations provided in [16]. Other than energy-related anomalies, this paper also considers operational anomalies. However, the daily operations in ICN is very different from what is written in the AIP data. For example, we can often find a certain runway being used in

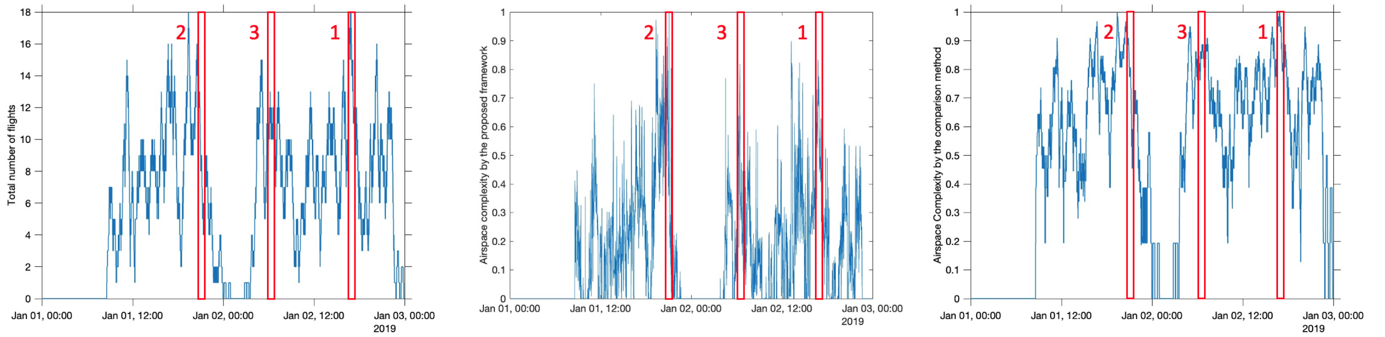

Figure 7: Total number of flights (left), complexity estimated by the proposed framework (middle), and complexity estimated by the comparison method (right)

irregular hours. Therefore, we include only go-arounds and holding flights as the operational anomalies in this paper. With more data available, more operational anomalies can be easily included.

Let the total number of flights in the airspace at time t be M^t, those having energy-related anomalies in the k^{th} feature, $k \in [1, N]$, be $M^t_{e_k}$, and those having operational anomalies be M^t_o. If a flight has both energy-related anomalies and operational anomalies, it is counted only once to avoid M^t_a being larger than M^t. We use the entropy from the information theory [28] and define the anomaly complexity C_a at every time step $t \in [T_{start}, T_{end}]$as:

$$\begin{aligned} C^t_a &= -\frac{M^t - M^t_a}{M^t} log \frac{M^t - M^t_a}{M^t} - \frac{M^t_a}{M^t} log \frac{1}{M^t} \\ M^t_a &= M^t_e + M^t_o \\ M^t_e &= \sum_{k=1}^{N} M^t_{e_k} \end{aligned} \tag{4}$$

The entropy measures the disorder of the airspace with respect to normal operations. If all flights are normal, the anomaly complexity is 0. The anomaly complexity C_a is normalized between 0 and 1.

IV. Results and Analysis

This section tests the proposed complexity estimation framework with arrivals in ICN between January 1 and 2, 2019. The sample time is 10 seconds, i.e., the complexity is estimated every 10 seconds from 00:00:00 on January 1 to 00:00:00 on January 3. For comparison, we select the airspace complexity measure proposed by Gariel et al. in [14] as the comparison method because it is the closest work that we can find in the literature. In [14], the airspace complexity is computed by the entropy contributed by outlier arrivals and fly-over flights. Note that we only consider arrivals in this paper for simplicity. Therefore, fly-over flights are excluded. Outlier arrivals are defined as flights that do not follow the procedures, flights that are on holding pattern, and flights that are executing a go-around. In ICN, flights that do not follow the procedures are flights that are identified into the vectoring pattern. For example, a non-vectoring pattern in GUKDO south is shown in Figure 8 where all flights follow the procedures, i.e., only execute a direct-to when they have

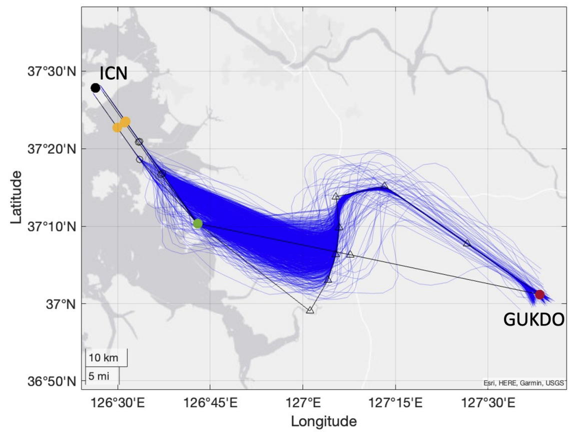

Figure 8: An example of non-vectored pattern

reached one of the direct-to fixes (fixes in the arc). Figure 7 shows the total number of flights, complexity in ICN terminal airspace between January 1 and 2 estimated by the proposed complexity estimation framework, and that estimated by the method proposed in [14]. Due to the large size of air traffic data, researchers need to read high-level figures such as those in Figure 7 to discover traffic situations with relatively high complexity. Therefore, we select three time intervals within the total time period for case study to test the benefits of the proposed framework. The three time intvervals are highlighted and numbered in red in Figure 7. The detailed complexity values of those three cases are presented in each case study.

The following subsections focus on the highlighted intervals for further analysis on the traffic situation and discussion. Consequently, the result shows our proposed complexity estimation framework can better represent the complexity in the RNAV terminal airspace than the number of flights and the comparison method.

A. First Case

The first case's time is between 16:48:00 and 16:58:00 in January 2 and the traffic situation is shown in Figure 9. The black lines are the RNAV STARs in ICN. Each flight is represented by a blue circle with a tail. The blue circle is the current position of the flight and the blue tail is the flight's position in the last 1 minute, so the flight's horizontal speed can be inferred from the length of the tail. As shown in Figure 10, the number of flights in this case is at the highest (18 flights). Therefore, to maintain the sequencing and separation, ATCs give a lot of vectoring commands. As shown in Figure 9, the flights coming from REBIT all travel in a straight line until they are close to merge with other flights, where they turn their heading to the Southeast. ATCs do so because the traffic volume from REBIT is heavier, and making flights travel in a straight line saves time so that the separation and efficiency are maintained. However, as a countereffect, the flights coming from other directions, especially OLMEN, need to be vectored in a path-stretch way to meet the required delays.

Although the traffic volume in this case is the highest, according to the complexity estimated by the proposed framework, this case is relatively not complex, as shown in Figure 10. This is because although all flights are vectored, most of them simply follow their preceding flights, especially in the West where the traffic is the heaviest. In this case, ATCs do not need to put much effort in their decision making process. Most of their attentions are actually paid into how to vector flights coming from other directions so that all flights merge smoothly. In addition, no anomaly is detected by the GMM anomaly detection model. Therefore, the real complexity and ATCs workload are not very high, which is accurately reflected by the proposed complexity estimation framework. In contrast, our comparison method shows a highest complexity due to all the vectoring flights.

B. Second Case

The second case is between 20:48:00 and 20:58:00 on January 1, and it is shown in Figure 11. The red flights are flights in holding patterns and the pink flights are anomalous flights that have energy-related anomalies which are detected by the GMM anomaly detection model. Note that some red flights do not show they are holding because they complete holding before 20:48:00. As shown in Figure 12, our proposed complexity estimation framework estimates a highest complexity. This is because there exist multiple holding flights (two of them from the same entry fix) and multiple anomalous flights. Although this case has less total number of flights (11 flights) than the first case, it has a much higher complexity because there is only one runway open, and in order to avoid runway congestions, ATCs need to hold multiple flights and make flights heavily deviate from the procedures. For example, the pink flight at 20:48:00 that seems to enter from KARBU actually enters from GUKDO, but it vectors to KARBU immediately after it enters the ICN airspace, and then it vectors back to GUKDO's STAR, which could be the reason why its specific total energy is anomalous.

Note that according to the AIP data, all runways operate between 20:48:00 and 20:58:00, but as shown in Figure 11, only one runway is in use, which suggests that there could be some situations at the airport such as a high number of departures that make other runways closed to arrivals. The comparison method estimates the complexity in this case lower than that of the first case, which is untrue as explained above. Researchers and ATCs can benefit from the proposed framework by investigating highly complex situations like this to discover more potential operational anomalies.

C. Third Case

The third case is between 6:23:00 and 6:33:00 on January 2, and it is shown in Figure 13. This case has much less number of flights than the first case, but is highlighted by the proposed framework in Figure 7 because as shown in Figure 13 at 06:25:00 and 06:29:00, the horizontal separation becomes too small twice (flights in the red circles). It can be seen that a large number of flights enter from GUKDO in a short period time and ATCs try to delay some of them so that a proper sequencing is maintained. However, it is not sure why the ATCs do not choose to vector some flight to KARBU like what they do in the second case or put some flights in the holding position. Possible reasons could be communication issues, pilot's nonconformance, or weather. In addition, this case shows that too many flights from the same entry fix could result in safety risks, horizontal separation being violated in this case, and ATCs responsible for sectors outside of ICN should take note of this and avoid such situations.

Note that although the comparison method computes a higher complexity than the proposed framework, it fails to highlight this case in Figure 7, i.e., the complexity in case 3 does not stand out enough to be noticeable. However, as discussed above, this case exists safety risks and therefore needs to be discovered and investigated. In general, the three case studies show that the proposed complexity estimation framework can highlight special situations better, which means it can estimate the complexity in RNAV terminal airspace more accurately than the comparison method and assist researchers and ATCs to discover potential traffic situation anomalies.

V. Conclusion

Area Navigation (RNAV) can improve the efficiency in the terminal airspace to meet the growing air traffic demand, but the terminal airspace becomes more complex than ever, especially for airports that widely adopt RNAV. In this paper, a new RNAV terminal airspace estimation framework was proposed. Unlike other terminal airspace complexity estimation methods, the proposed framework, for the first time in the literature, considers vectoring patterns, aircraft separation, and anomalies together. Each component in the proposed framework modifies and implements our previously developed algorithms, i.e., trajectory pattern identification and classification, multi-agent trajectory prediction, and Gaussian mixture model-based anomaly detection. The total complexity is defined as a linear combination of the vectoring complexity, the separation complexity, and the anomaly complexity. The proposed framework was tested with the Automatic Dependent Surveillance-Broadcast (ADS-B) data recorded in the Incheon International Airport in South Korea between January 1 and 2 in 2019, and the Aeronautical Information Publication data. Three case studies were performed to show the advantages of the proposed framework over the comparison method. The result showed that the proposed framework can help researchers and air traffic controllers discover operational

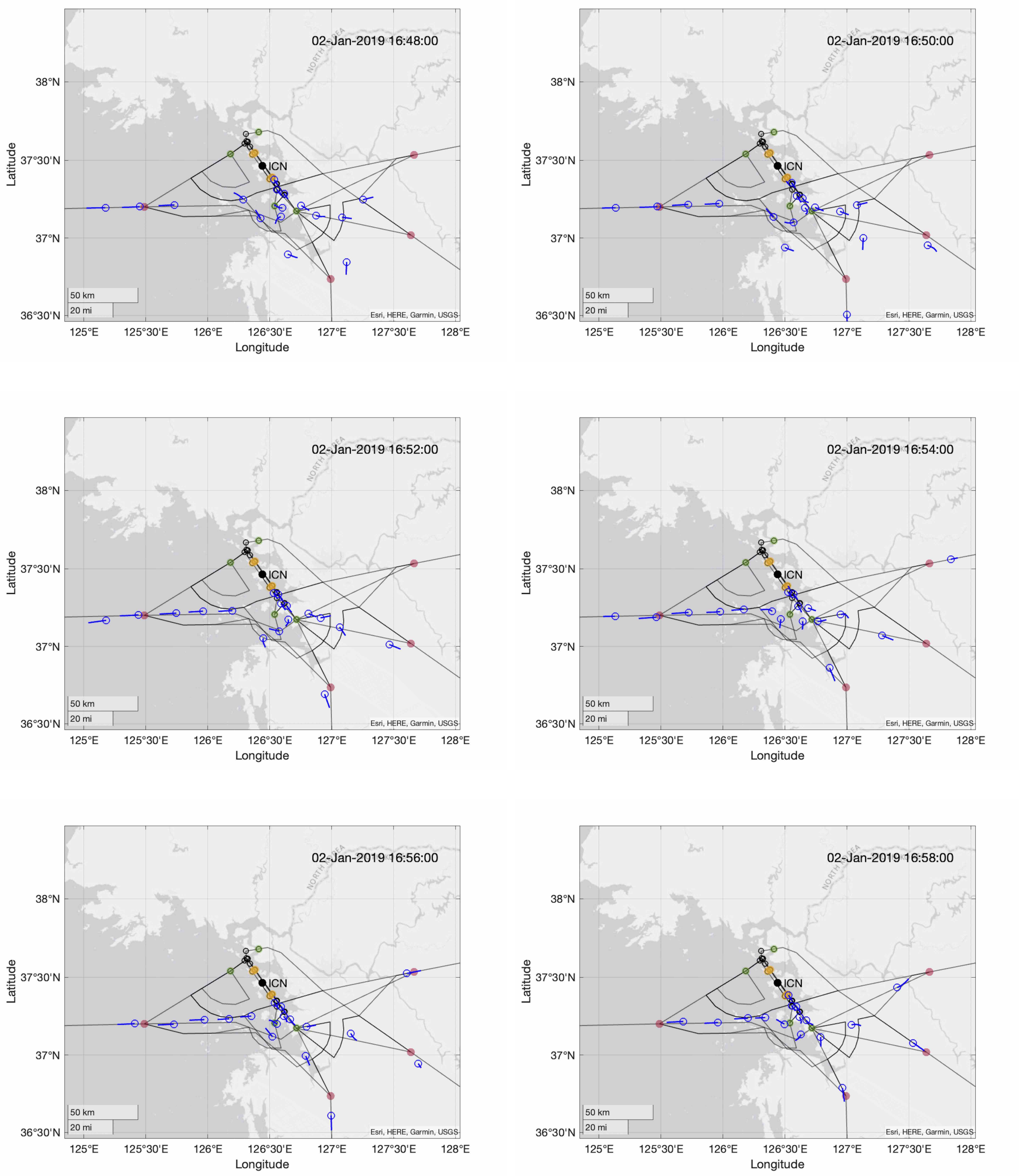

Figure 9: First case

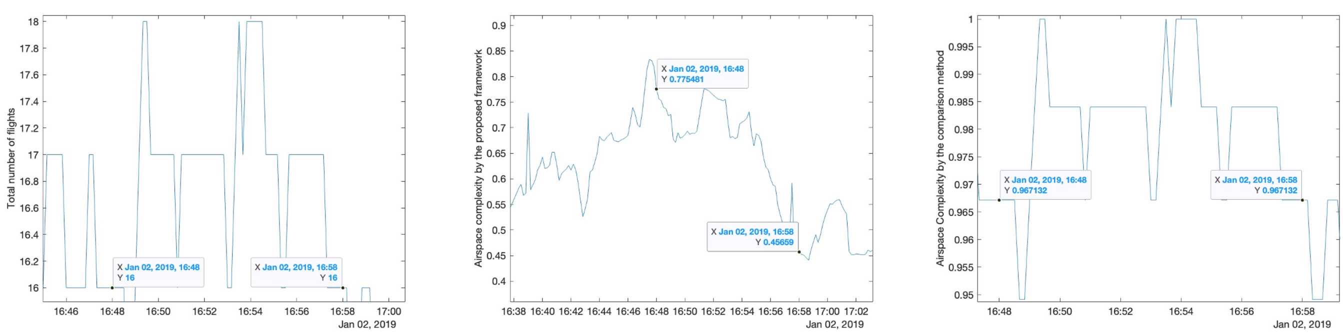

Figure 10: Airspace complexity of the first case estimated by the three methods

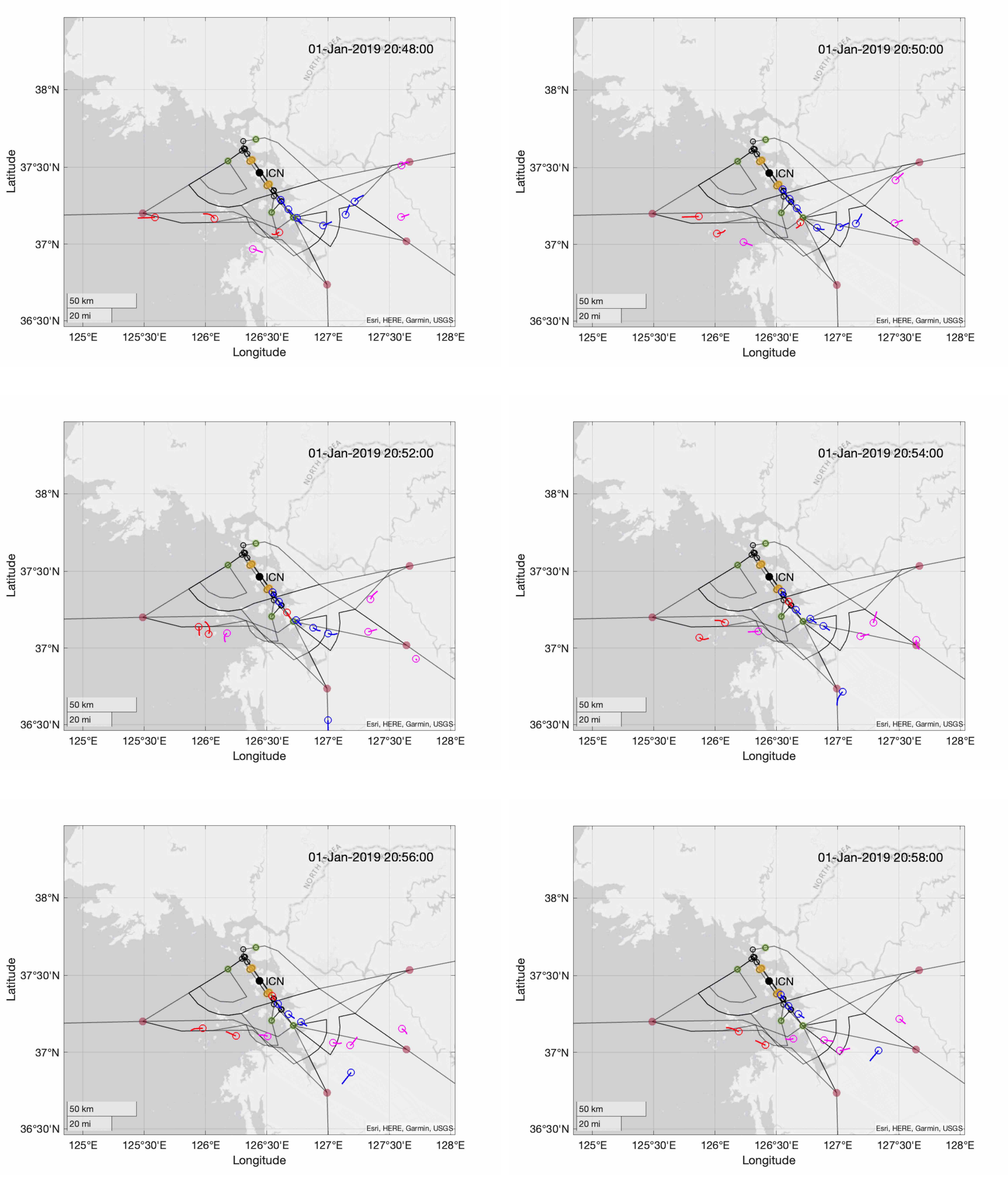

Figure 11: Second case

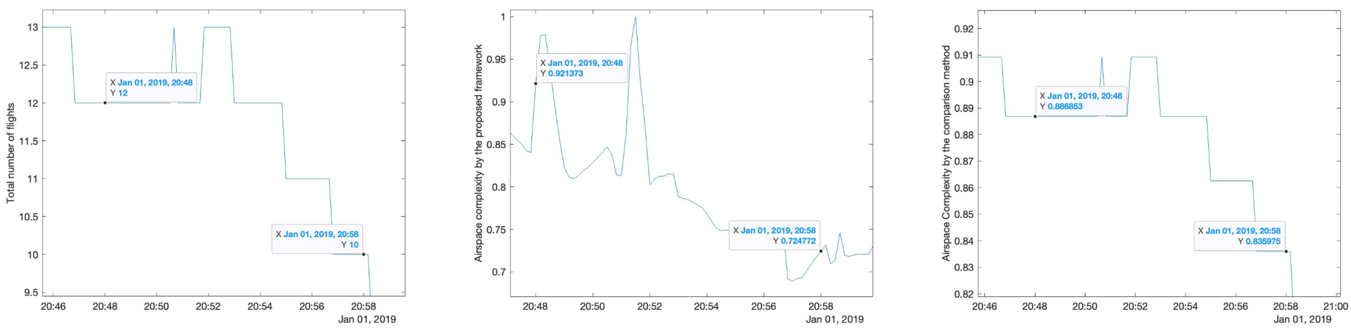

Figure 12: Airspace complexity of the second case estimated by the three methods

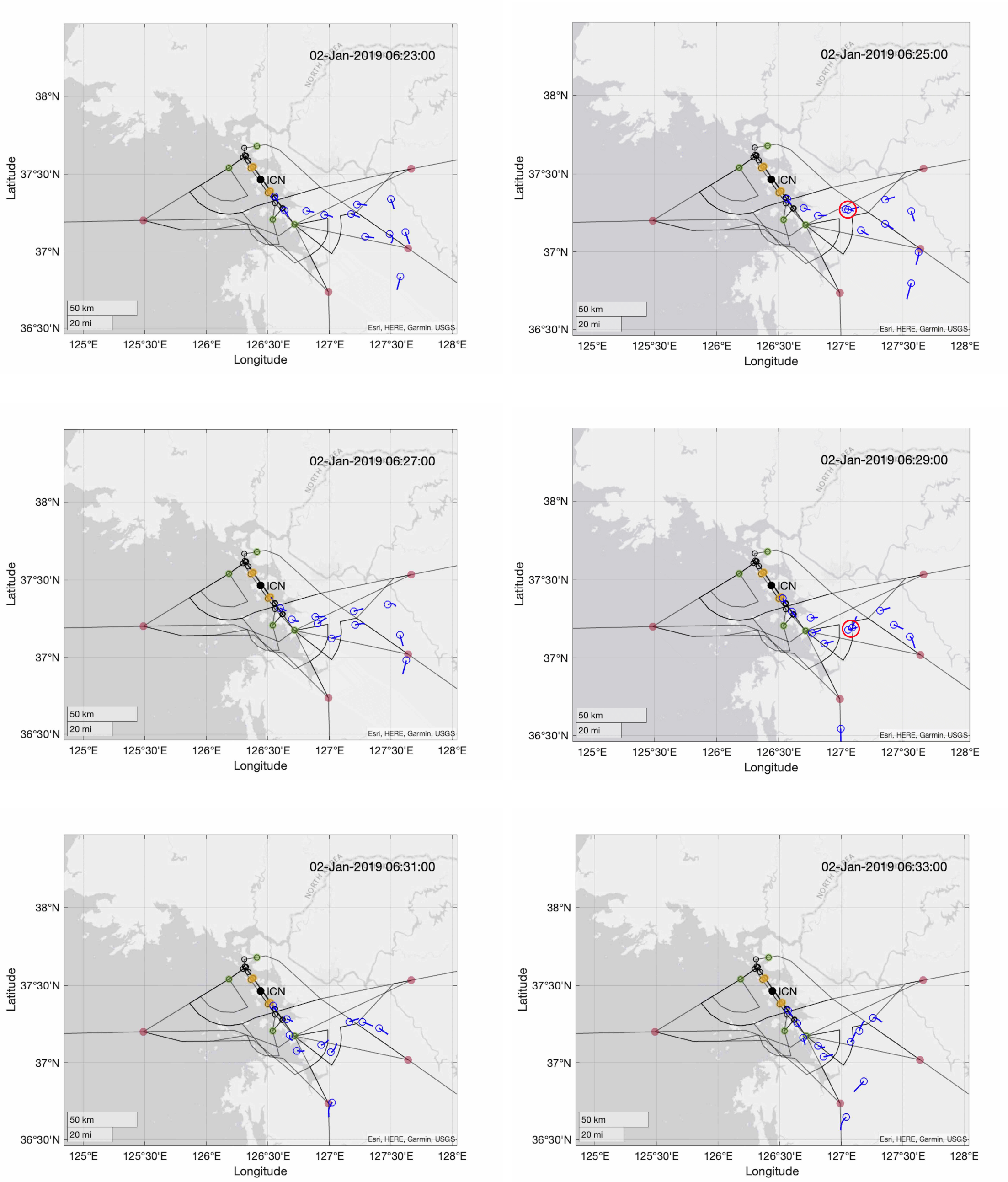

Figure 13: Third case

anomalies that may be overlooked and improve the safety of the RNAV terminal airspace.

Note that the proposed complexity estimation framework has the following limitations: (i) Only arrivals are considered. Although based on our study, arrivals are more complex than departures, including departures can deliver a more complete picture of the airspace. (ii) Only ADS-B data are used. If more data such as ground operation data were available, we may be able to explain some high-complexity situations such as the second case. (iii) The proposed complexity estimation framework has not been validated by feedback from real air traffic controllers, which could change the coefficient of each complexity component or add more complexity components. The limitations are considered as our future work and will be studied to improve and further validate the proposed framework.

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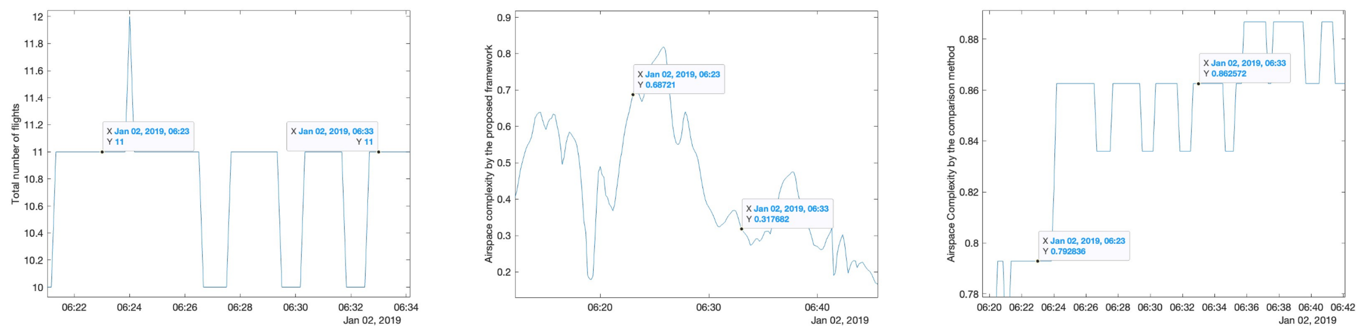

Figure 14: Airspace complexity of the third case estimated by the three methods

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