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# Extracting Lateral Deconfliction Actions from Historical ADS-B data with Median Regression

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**Abstract**—Air traffic controllers (ATCO) work in an uncertain environment where they operate traffic with a double objective of minimizing flight times while ensuring safe separations, i.e., detecting and solving trajectory conflicts. They constantly face uncertainties because of variable weather conditions, aircraft speeds, or pilots response time. The development and acceptance of decision support tools to help controllers perform a safe separation must account for these uncertainties and align with operational practices to ensure satisfactory user adoption. In this paper, we build upon a previously published dataset of actual conflict resolutions based on historical ADS-B data and flight plans. In this previous work, we proposed a heuristic to detect deconfliction situations among aircraft persistently deviating from their intended route. Here, we extend our approach to previously overlooked areas of the data. In particular, we apply a KNN-Median regression approach to additional explanatory variables, and gain more insight in the way ATCO cope with potentially conflicting traffic. The most significant improvement is the ability to extract deconfliction situations leveraging “direct-to” instructions.

**Keywords**—deconfliction; information extraction; ADS-B

## I. INTRODUCTION

Managing safe and efficient operations in air traffic management is a difficult and complex task. One of the main duties of ATCO is to detect and resolve trajectory conflicts occurring in the airspace under their responsibility, and issue necessary instructions to pilots to maintain proper separation. Every pair of aircraft must maintain a safe lateral and vertical separation at any moment. The separation standards in the upper airspace are 5 nautical miles (NM) laterally, and 1,000 feet vertically. A simultaneous violation of both constraints results in a loss of separation which is a contributing factor for mid-air collision.

The critical task of detecting conflicts (i.e., anticipating separation losses) and solving them is still currently performed by human operators. Many conflict detection and resolution algorithms have been proposed in the literature, that could assist the controllers in these tasks. However, the effectiveness of these tools depends not only on their technical performance but also on their acceptance among controllers. This acceptance requires alignment with the cognitive processes inherent to their operational practices.

Controllers have to deal with uncertainties on a variety of parameters such as speed, wind velocity and pilots’ reaction times, necessitating a critical margin of error in the separation they maintain. For this reason, the standard separations alone do

not constitute satisfying thresholds for deconfliction. Aligning with their work practices implies accurately estimating these uncertainties and integrating them into decision-support tools.

Learning controller uncertainty models from data can be done using datasets of deconflicted traffic situations. In [1], a genetic algorithm is used to extract uncertainty models from artificial or small experimental datasets. A motivation of our study is to build large real-life datasets of deconflicted traffic situations that could be used to learn realistic uncertainty models, or to identify usual resolution strategies, among other potential purposes. In a previous study [2], we proposed a heuristic method to extract from historical ADS-B data the lateral trajectory deviations resulting from deconfliction actions performed by ATCO. This heuristic approach was based on the detection of lateral trajectory deviations, i.e., trajectory segments not aligned with a navaid of the intended route, and considerations on the predicted lateral separations between neighbouring flights.

The threshold value allowing us to decide whether a lateral deviation results from a deconfliction action was determined using a KNN-Median Regression on the difference between the actual and predicted separations. The idea was that lateral deviations unrelated to deconfliction actions are as likely to decrease the separation as to increase it, resulting in median values close to zero. Conversely, lateral deviations resulting from a deconfliction are expected to increase the separations with the neighbouring aircraft, and to exhibit strictly positive median values. This analysis allowed us to determine a threshold value of 8 NM for the predicted separation between two neighbouring flights, below which a lateral deviation is considered as resulting from a deconfliction. This means that controllers are more inclined to perceive a situation as potentially hazardous when they anticipate that, without intervention from their part, it could result in a separation falling below this threshold. Our previous study focused on long deviations only and did not consider deconfliction actions such as “direct-to” instructions, which do not result in persistent lateral deviations.

In this study, we extend the analysis to other variables, in particular the duration of the lateral deviation, and the time to the closest point of approach (CPA) before combining them with our 8 NM threshold on the predicted separation. The objective is to filter out short deviations related to usual trajectory turns from the short deviations related to a “direct-to” instruction.

The remainder of the paper is structured as follows: In Sec-

tion II, we establish the background and context of our research. The methodology employed to extract the dataset and perform median regression is detailed in Section III. The results of our study are presented in Section IV. Finally, in Section V, we conclude with a summary of the main findings, and perspectives for further research directions.

## II. CONTEXT AND LITERATURE REVIEW

Solving air traffic conflicts requires conflict detection, which itself relies on the availability of accurate trajectory predictions. Prior works on trajectory prediction for conflict detection and resolution introduced a variety of models, including polygonal zones modelling the speed, time, and direction uncertainties of manoeuvred aircraft [3], probabilistic models of the predicted trajectory [4], [5], confidence intervals [6], and specialized machine learning models for time-series data [7].

Detecting conflicts can be done in different ways, depending on the underlying trajectory model. In a probabilistic framework [4], [5], a probability of conflict is computed from the probabilistic trajectory predictions, and conflicts can be considered as critical beyond a certain probability threshold. When using polygonal zones around nominal trajectory predictions [3], conflicts are detected when the uncertainty zones come closer than the standard separation. Some machine learning methods bypass trajectory prediction entirely. For instance, in [8], conflicts and critical scenarios are simulated by modifying historical ADS-B data from the OpenSky Network, with machine learning employed to predict conflicts among the extracted trajectories.

Concerning conflict resolution, several methods have been proposed in the literature. For instance, in [9], [10], mixed-integer programming is applied to find optimum conflict resolutions, without considering trajectory prediction uncertainties. In [11], the conflict resolution problem is modelled as a minimum weight maximum clique problem and solved with a mixed-integer linear programming method, without taking uncertainties into account. Other approaches, such as Evolutionary Algorithms (AE) [12], [13] or Ant Colony optimization [14] do not guarantee the optimality of the solutions, but can compute good solutions within a limited time budget. They can also easily accommodate more realistic uncertainty models. In [15], A Constraint Programming approach is compared with an Evolutionary Algorithm, taking speed and lateral uncertainties into account, using pre-computed lateral manoeuvre combinations.

The above methods mostly address the conflict resolution problem as an optimization problem—find the shortest path to destination while avoiding conflicts—and heavily rely on mathematical modelling. Other data-driven approaches focus on the manoeuvres issued by the controllers, or their actions in general, using large real-life datasets of past aircraft trajectories. This is the case for [16] which uses unsupervised learning, or [17], an approach based on the use of an auto-encoder architecture and reconstruction error.

Developing decision tools to provide solutions to conflict resolution problems raises acceptability issues. Human ATCO are more likely to accept solutions that align with their own thought process [18], [19]. Consequently, they might be more

prone to reject automated tools proposing solutions that do not align with their usual practices and internal representations. Several approaches have explored the possibility to use Machine Learning to produce more realistic deconfliction suggestions. For example, [20] uses a reinforcement learning method based on deconflictions performed by real ATCO on simulated conflicts, whereas [21] uses imitation learning with the objective to learn from deconfliction manoeuvres in historical data.

In [1], a genetic algorithm is used to learn the uncertainty parameters of the trajectory prediction, using datasets of examples of conflict resolutions. On artificial data with known uncertainties, this method was able to find the lateral and speed uncertainty parameters that were used to produce the data. It also showed promising results on small datasets of human-made resolutions obtained from real-time experiments. However, it has not yet been experimented on large real-life historical datasets of conflict resolutions, due to the unavailability of such data.

In [2], we made a first attempt at extracting such a dataset from historical ADS-B and flight plan data. This previous study focused on persistent lateral deviations from the intended route, and characterized them as resulting from deconfliction actions when the closest predicted separation with the neighbouring traffic fell below a certain threshold and when the deviation resulted in an increased separation. A KNN-Median regression method allowed us to extract the value of the separation threshold (8 NM) from the data, based on considerations on the median value of the difference between the actual and predicted separations, as stated in the introduction.

Here, we focus on small, non-persistent lateral deviations from the intended route, and extend our median analysis approach to other variables to identify which of these deviations are just routine turns between successive segments of the route, and which ones might be more likely related to “direct-to” instructions issued by a controller to avoid a conflict.

## III. METHODOLOGY

### A. Dataset

This study builds upon the foundation laid by [2], utilizing the same ADS-B dataset corresponding to the AIRAC cycle 2207 (July 14 to August 10, 2022) within the bounds of the Air Control Center of Bordeaux, France (LFBBBBDX). This dataset was sourced through the OpenSky Network [22]. Flight plan data and navaid information were provided by the Air Navigation Services and integrated into this dataset. Each flight is uniquely identified and linked to its respective flight plan.

Formatting and manipulations on the dataset were carried out using the Python library *traffic* [23]. Flights were filtered out of anomalous data, resampled to one point per second to ensure seamless operations between flights, and then filtered to retain only portions within the bounds of Bordeaux ACC and above 20,000 feet (FL 200).

Flights were then matched with their corresponding flight plans, and segments of trajectories aligned with a navigational beacon (navaid) were labelled accordingly. The complete filtered and resampled dataset contains 78,316 different trajectories.

## B. Deviations from the flight plan

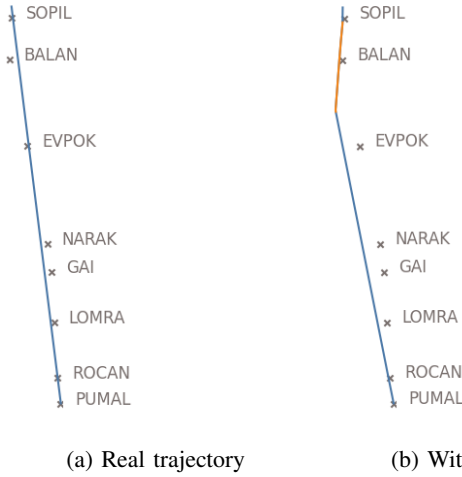


Figure 1: Two trajectories associated to the same flight plan.

The extraction of deconfliction actions relies on observing deviations from the flight plan. It is typical in normal traffic for aircraft to skip certain navaids in the flight plan, resulting in flown trajectories that may not precisely align with their initial flight plan. This is illustrated in Figure 1.

Both trajectories 1a and 1b are associated with the same flight plan SOPIL BALAN EVPOK NARAK GAI LOMRA ROCAN PUMAL. Although 1a does not successively align with each navaid in its flight plan, it remains aligned with one of its navaids at all times. This pattern is normal and should not be associated with any abnormal event. For this reason, we consider a deviation from the flight plan to be significant only if the aircraft is not aligned with one of the navaids in its flight plan, indicating an abnormal deviation from the expected trajectory and suggesting an unexpected event. In Figure 1b, the orange portion shows a typical example of a deviation as they are considered in this paper. During these deviations, the aircraft either aligns with a navaid that is not in its flight plan, or it does not align with any navaid. Given the paper’s focus solely on lateral deviations, we minimize the risk of introducing a potential vertical component in deconfliction by exclusively extracting deviations where the aircraft maintains a stable altitude within a threshold of 50 ft.

To ensure accuracy during the alignment check, we limit our consideration to navaids from the flight plan that are within a distance of 200 NM, with a precision angle of 2 degrees. In [2], we focused only deviations longer than 120 seconds, assuming that those below this threshold corresponded to standard turns in the trajectory.

In Figure 2, we provide an illustration of a deviation identified as a standard turn on the left, and on the right, a deviation long enough to be incorporated into our earlier analysis. Short deviations are very common in normal traffic and typically correspond to standard turns in trajectories.

In this paper, we suspect that some of these short deviations might be “direct-to” instructions could also be used to resolve conflicts. To test this hypothesis, we lower our duration threshold

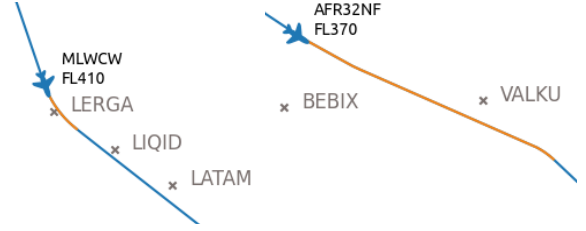


Figure 2: Example of a short deviation corresponding to a turn in the trajectory (left), and of a longer deviation (right), with deviated portions in orange

to include all deviations longer than 30 seconds, which will be analysed in the following sections. The resulting dataset contains 14,610 deviations.

## C. Relation to surrounding traffic

Although we may attribute the lateral deviations extracted from the trajectories to unexpected events, these may not necessarily be linked to conflict resolution manoeuvres. To determine whether a deviation was initiated to resolve a conflict or not, we assess it in the context of potential interactions with surrounding traffic.

Let us consider aircraft  $A$  with the lateral deviation starting at  $t_1$  and ending at  $t_2$ . Since there is no indication that the deviation is inherently intended to resolve a conflict occurring before its conclusion, we will analyse the trajectory from  $t_1$  up to a maximum time horizon of  $t_1 + \tau$ , with  $\tau = 20$  minutes. This horizon can be adjusted if aircraft  $A$  exits Bordeaux ACC airspace before  $t_1 + \tau$  or if a significant altitude change occurs. Focusing solely on the stable portion of the deviation helps eliminate bias introduced by the vertical component.

For another aircraft trajectory  $B$  to be deemed potentially problematic for flight  $A$ , it must intersect the horizontal plane where the deviation for  $A$  occurs within a relevant time frame. However, aircraft  $B$  may not consistently fly at the same altitude throughout this period. For example, it could simply intersect with  $A$ ’s horizontal plane while ascending or descending to another flight level. Since  $B$ ’s altitude can vary significantly between  $t_1$  and  $t_1 + \tau$ , we consider only segments of  $B$ ’s trajectory within a specified altitude range around  $A$ ’s altitude. Ignoring irrelevant segments also implies that the examined trajectories cannot be resampled without adding bias to the analysis, therefore they may not be continuous. In this study, we use an altitude interval of  $\pm 50$  ft around  $A$ ’s altitude.

Following this logic, each deviation extracted from our original dataset will be associated with a set  $\mathcal{N}$  of potentially relevant neighbouring trajectory portions that meet the following criteria, for each portion  $p$ :

$$t_1 < p.\text{timestamp} < \min(t_2, t_2 + \tau) \quad (1)$$

$$\text{dev.altmin} - \text{margin}_{\text{alt}} < p.\text{altitude} < \text{dev.altmax} + \text{margin}_{\text{alt}} \quad (2)$$

Controllers evaluate the risk of conflict by forecasting future aircraft trajectories and their potential closest points of approach.

This entails identifying scenarios where an aircraft, denoted as  $A$ , is deviated to avert a conflict, suggesting the presence of another aircraft, denoted as  $B$ , that would have been too close had the deviation not occurred. In our prior study [2], we assumed that if aircraft  $A$  was deviated to resolve a conflict with  $B$ ,  $B$  would remain the closest aircraft to  $A$  in the final trajectory, although further away than it would have in the absence of deviation. Once  $B$  was identified, we used its trajectory to predict the closest separation that would have occurred without the deviation order and assess the possibility of conflict as perceived by the controller.

However, there is no guarantee that, if  $A$  was deviated to resolve a conflict, the initially avoided aircraft  $B$  would remain the closest upon completion of the manoeuvre. Depending on the extent of the deviation and the traffic geometry, another aircraft could theoretically present a conflict without necessarily being the closest to the final trajectory.

In this study, we opted to directly identify  $B$  as the trajectory that comes closest with the prediction of  $A$ 's trajectory in the absence of the deviation. This adjustment is expected to mitigate any bias in our analysis related to the choice of the potential conflicting trajectory.

#### D. Conflict risk estimation

Once we identified a deviation along with the corresponding neighbouring trajectories that might be the cause for a conflict resolution manoeuvre, we need to estimate the risk that a conflict would have occurred in the absence of the deviation.

Using the flight plan information, we simulate the trajectory starting just before the deviation, when the trajectory was still aligned on one of the navaid in its flight plan. The simulated trajectory  $\hat{A}$  maintains this alignment until it reaches the navaid, then follows precisely the rest of the flight plan without skipping any navaid, until  $t_2 + \tau$ . The predicted speed is constant throughout the simulation and corresponds to the aircraft's average speed from the last 20 minutes before it was deviated. Turns are considered to occur instantaneously upon reaching each navaid, no physical constraints are considered. We consider that the aircraft maintains the altitude it had before deviating.

This is where our approach differs slightly from [2], which estimated the predicted closest separation with the aircraft that was the closest to the real trajectory. Here, we compute the closest separation between the predicted trajectory and all the neighbours in  $\mathcal{N}$ . The selected neighbour  $B$  will be the one with the closest minimum separation relative to the predicted deviation-free trajectory.

In Figure 3,  $A$  is the blue trajectory, deviated on the orange portion to avoid  $B$ , the green trajectory. This deviation lasts 7.15 minutes. The flight plan's navaid are located by blue crosses, and the grey-dashed line represents the prediction over 20 minutes, starting right before the deviation. On the visible portions, both trajectories are on FL 370 i.e., 37,000 ft. All three plotted aircraft represent the position in each of the three trajectories at the same time, which is the time when the separation between TUI87H and RYR8J would have been the closest without deviation.

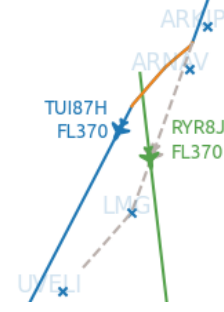


Figure 3: Example of a detected deconfliction situation, with the deviated trajectory in blue, the closest neighbouring trajectory in green and the predicted trajectory in grey.

The closest separation between TUI87H and RYR8J, a.k.a.  $\min s$  is 19 NM, which is largely above the minimum lateral separation of 5 NM. However, the overlapping grey and green aircraft indicate that, in the absence of the deviation, a loss of separation would have occurred. In this case, the closest predicted separation  $\min \hat{s}$  is 2 NM.

It is also apparent that, after the deviation, TUI87H does not align to the closest navaid in its flight plan, but skips some of them to align with a navaid that is further away. As mentioned in Section III-B, this is not an abnormal behaviour, but underlines the inexactitude of the flight plan-based prediction. Although it gives us more nuance than a simple straight-line prediction would, it may still be unrealistic in some situations.

Figure 3 gives a very clear example of deconfliction. Many of the extracted deviations do not show such an obvious pattern. Deviations which bring aircraft closer together, for example, are not viewed as involved in a deconfliction action. However, an increase of the closest separation between aircraft is not a sufficient criterion, as  $\hat{A}$  and  $B$  could be distant enough for the risk of loss of separation to be considered null. Following this logic, in [2], we consider a situation as a resolved conflict if it fits these two criteria:

$$\min \hat{s} < \min s \text{ and } \min \hat{s} \leq S = 8 \text{ NM} \quad (3)$$

With  $S$  a threshold which represents the minimum separation tolerated in practice, under which a controller would order a separation manoeuvre. In an ideal scenario, with no additional uncertainties inherent to controllers' practices,  $S$  would be set to the minimum lateral separation of 5 NM. A threshold close to this minimum value would reflect a high-risk tolerance of the operator in a given situation. Conversely, a much higher value of  $S$  would indicate a more cautious operator. Our objective is to estimate a realistic value for  $S$  that accounts for the added uncertainties faced by controllers. It's important to note that each controller may have different thresholds, and various situations may lead to different values for  $S$ . In the future, we plan to use our dataset to better understand specific patterns associated with these various controllers' profiles.

### E. KNN algorithm

K-nearest neighbours (KNN) is a simple supervised learning algorithm often used in classification and regression tasks. The prediction for a given data point is computed by averaging the target variable values of its  $k$  nearest neighbours in the feature space. Closeness between data points in the feature space is typically measured using a distance metric such as Euclidean distance. This method leverages the idea that similar data points tend to have similar target variable values, making it a straightforward yet effective approach for regression tasks. The choice of the parameter  $k$  determines the trade-off between bias and variance in the model. A smaller value of  $k$  leads to a more flexible model with higher variance but lower bias, while a larger value of  $k$  results in a smoother prediction with lower variance but potentially higher bias.

### F. Median regression applied to conflict detection

Deconfliction manoeuvres aim to increase the separation between conflicting trajectories. On the other hand, unrelated manoeuvres are not expected to follow this pattern. If a manoeuvre is detected in a low-risk context where the predicted closest separation is significantly high, we anticipate that it would have an equal chance to either increase or decrease the closest separation. Among the extracted deviations for which the closest separation is above the acceptable risk threshold  $S$ , we thus expect there to be roughly the same number of deviations increasing the separation as there are decreasing it. Consequently, the median variation in separation should be close to 0. When the separation falls below  $S$ , the increase should be strictly positive, with higher values indicating an increased risk and aiming to maintain the separation above 5 NM, ideally exceeding  $S$ . To verify this intuition formally, we use a K-nearest neighbours (KNN) median regression method with  $k=100$  neighbours, which extends the conventional KNN algorithm. In our context, the model predicts the median value of the difference between the actual and predicted closest separation, leveraging the predicted closest separation values.

## IV. RESULTS

### A. Previous findings

In Figure 4, we depict all the extracted situations involving deviations lasting 30 seconds or more. Each point in the scatter plot represents a deviation, with the x-axis denoting the predicted closest separation, and the y-axis indicating the increase in separation between the actual and predicted closest separations.

The black line corresponds to the median of the difference according to the predicted closest separation, as described in the methodology above. The green-dashed line represents the equation  $y = 5 \text{ NM} - x$ , meaning all points above this line represent situations for which  $\min s > 5 \text{ NM}$ . Points above this line indicate situations where the separation remains above 5 NM. Conversely, points below the green line imply actual losses of separation. Upon closer examination, it becomes apparent that these occurrences are probably inconsistent, resulting from data noise, rather than genuine instances where  $\min s < 5 \text{ NM}$ .

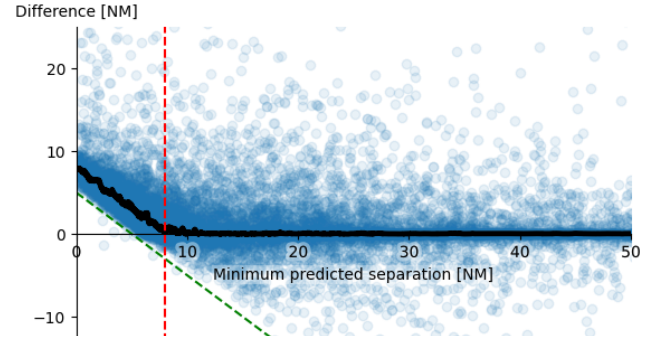


Figure 4: Difference between actual and predicted minimum separation as a function of the predicted closest separation. The red-dashed line crosses the x-axis at 8 NM and the green-dashed line at 5 NM.

With the vertical red-dashed line, we represent approximately the point at which the median drops to 0 : it crosses the x-axis at a significant value for our threshold  $S$  around 8 NM. Below this threshold, the median difference consistently follows a linear trend with the equation  $y = 8 \text{ NM} - x$ . For values predicted closest separations above 8 NM, the median stagnates around 0. This observation validates the hypothesized pattern and establishes a threshold of  $S = 8 \text{ NM}$ . Throughout the remainder of this work, we regard this threshold as indicative of acceptable risk from the controller’s perspective, signifying that deviations below this value are most likely caused by deconfliction actions.

### B. Analysis on duration criteria alone

Since the median regression showed interesting results for determining the separation threshold, we now explore whether we can employ a similar methodology on other criteria. In this section, we aim to establish a threshold for the minimum duration of a deviation required to be considered a pertinent candidate for conflict resolution.

Applying the same reasoning as previously, we consider that if standard turns are unrelated to deconfliction manoeuvres, they should neither increase nor decrease the minimum separation between aircraft. Consequently, we expect to observe a median value close to zero for small duration values.

In Figure 5, we represent the difference in minimum separation made by the deviation according to its duration, with the median regression on 100 neighbours as a black line. The red-dashed line corresponds to the 120-second threshold used in [2].

We observe a highly concentrated, roughly symmetrical cluster for small values, which we hypothesize to be typical minor deviations associated with turns in the trajectory. For this segment of the cluster, the median is close to zero, signifying that deviations with these duration values are unlikely to either increase or decrease the minimum separation. This aligns with normal turns in the trajectory, which would be unrelated to deconfliction manoeuvres. Up until a certain point, where data becomes sparser, longer deviations are more likely to increase the separation between aircraft than smaller ones. This result appears to confirm that situations below 120 seconds are ir-

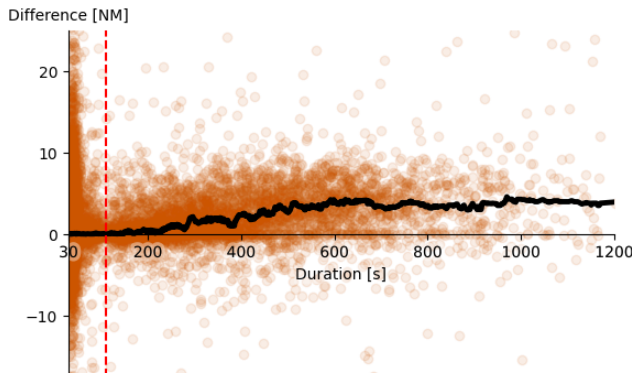


Figure 5: Difference between actual and predicted minimum separation as a function of the duration of the deviation

relevant and should not be regarded as potential deconfliction manoeuvres. Considering the shape of the graph and depending on the desired precision level, there could be room to extend this threshold beyond 200 seconds.

Though it is technically possible to redirect an aircraft's alignment to another navaid to resolve a conflict, we do not observe this trend in Figure 5. However, the point cloud around short values for duration is very dense and, if this phenomenon exists, it could be obscured by the sheer number of deviations corresponding to standard turns. To explore this possibility further, we conduct median regression analysis on the duration of deviations occurring in high-risk scenarios, where the closest predicted separation is below the threshold  $S$ .

C. Combination of thresholds on separation and duration

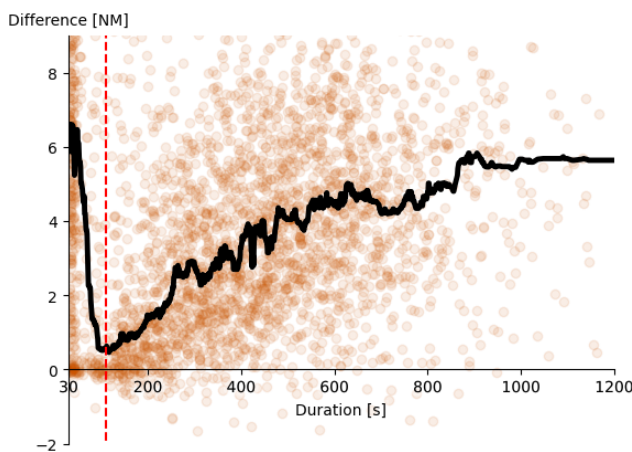


Figure 6: Difference between actual and predicted minimum separation as a function of the duration of the deviation, after applying the 8 NM threshold to the point cloud

Applying the  $S$  threshold to our initial deviations dataset results in the selection of 3,136 deviations. Visualizing the impact of duration factors specifically for instances with a higher risk of loss of separation, as shown in Figure 6, reveals a distinct

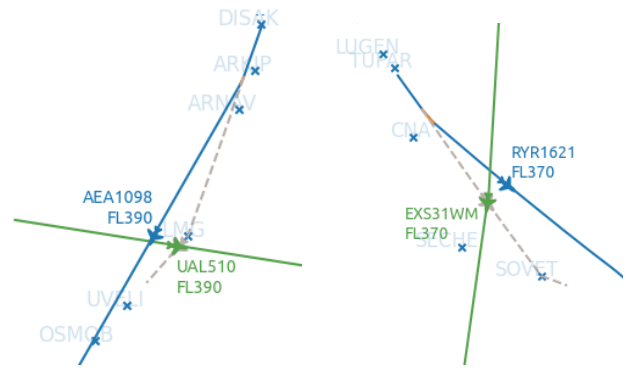


Figure 7: Examples of two detected deconfliction situations resolved with “direct-to” manoeuvres

median profile, particularly for short deviations. Notably, the median value peaks around durations of 30 seconds.

The arrangement of this point cloud implies the presence of two distinct types of deconflictions in our dataset, some involving small deviations below 110 seconds and others featuring longer deviations. We call this threshold for duration  $D$ .

Out of the 9,583 points in the original cloud for which the duration is inferior or equal to  $D$  seconds, 492 points are below the threshold of 8 NM for predicted minimum separation, selecting only 5.1% of short deviations as potentially relevant in deconfliction. This low percentage explains why this trend was not detectable in Figure 5.

Figure 7 shows two examples of situations for which a small deviation was detected and seems to be related to a deconfliction. In these instances, the closest neighbouring aircraft was not deviated. The absence of the detected deviation would have resulted in a loss of separation with a minimum distance of 2.9 NM on the left, and 0.4 NM on the right. These two examples confirm the existence of a type of deconfliction that leverages direct manoeuvres to resolve conflicts.

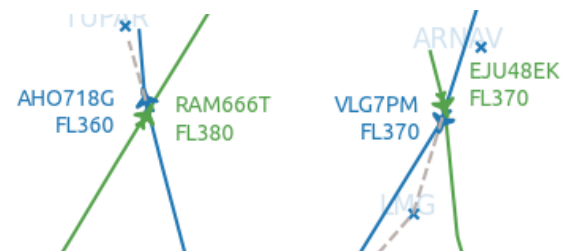


Figure 8: Two false positive examples

The compact zone around difference values of 0 in Figure 6 implies that, even though the median is positive for small values, a number of situations in this zone may still be unrelated to conflict resolution. Therefore, small deviations with no connection to deconfliction are expected to remain in the dataset. Figure 8 illustrates two such scenarios, where the difference value is minimal, with 0.2 on the left and 0.1 on the right.

An examination of these scenarios suggests that they are not associated with deconfliction actions. In the first case, the

green trajectory is deviated in a manner that suggests conflict resolution. In the second case, the deviation is initiated at a time when the aircraft are already moving away from each other. This observation not only confirms the hypotheses presented in this section, but also underling new criteria that will be discussed and integrated to enrich our model in future research.

The conjugation of two different thresholds extracted with a median regression on the difference made in separation by the deviation revealed a type of deconfliction we had not considered in previous research. However, the resulting dataset still contains occurrences which are likely unrelated to deconfliction. In the next subsection, we introduce a new variable to enhance our analysis and filter out more negative instances.

#### D. Threshold on time to CPA

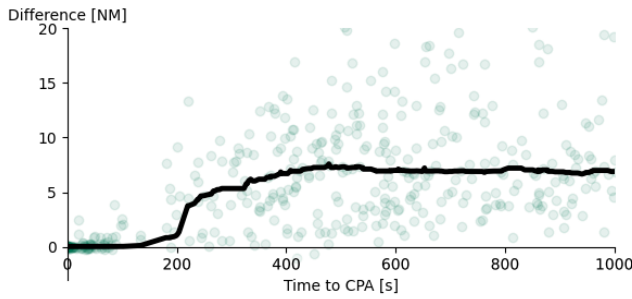


Figure 9: Difference between actual and predicted minimum separation as a function of  $t_{CPA}$ , after applying the heuristic to the point cloud and a criterion of duration  $< 110s$

This time, we start from a dataset containing deviations with a duration  $< D$  and with  $\min \hat{s} < S$ . Within this dataset, we identify an interesting pattern associated with the time to CPA. The time to CPA, denoted  $t_{CPA}$ , is defined as the total duration between the initiation of the deviation and the moment of the CPA between the predicted trajectory and the closest neighbour, where the predicted separation is minimal. Again, we use a KNN-Median regression on the values of difference, this time according to  $t_{CPA}$ . The results are shown in Figure 9.

We identify a dense cluster of points corresponding to a median value for difference around 0 NM, which shows that, for this specific dataset, instances for which  $t_{CPA}$  is under 150 to 200 seconds are unlikely to significantly increase or reduce the minimum separation between the aircraft.

We set the threshold  $T_{CPA}$  to 200 seconds and use it to filter the data, which removes 100 trajectories from the dataset. After successively using three thresholds determined through three median regressions using different variables, our final dataset contains 392 occurrences. Figure 10 (page 7) shows a comparison of the distribution of the datasets for  $t_{CPA} < T_{CPA}$  (blue) and  $t_{CPA} \geq T_{CPA}$  (orange).

This comparison shows that the newly eliminated 100 trajectories form a dataset with a median for difference close to 0, suggesting an unlikely link with conflict resolution. Still, a few points are characterized with a higher value, showing that some of the more relevant situations were also excluded by the

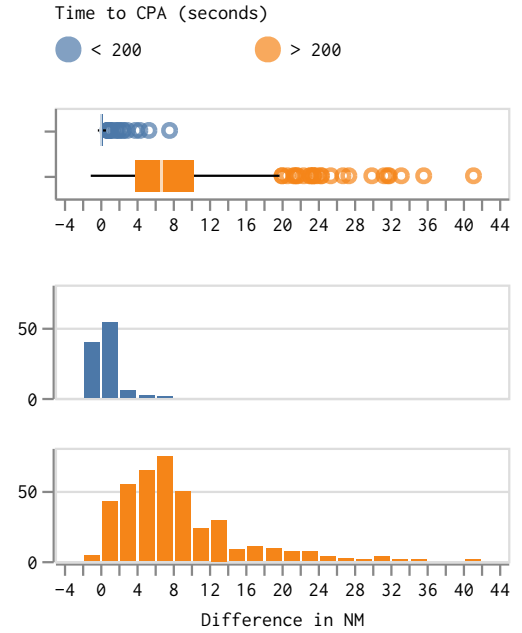


Figure 10: Distribution of the difference according to  $t_{CPA}$

application of threshold  $T_{CPA}$ . Some of these could be included back by lowering the threshold, with the risk of including some irrelevant instances.

#### E. Visual inspection of the resulting dataset

In the final step of our study, we conduct an inspection of our results. With a final dataset containing 392 occurrences, we are able to undertake a comprehensive visual examination. Within this dataset, we identify 56 occurrences that are either unmistakable false positives or too ambiguous to draw conclusions from. Better conclusions might be obtained with the help of ATC experts, but at this stage, we determine that our method achieves an accuracy rate of approximately 85.7% on our dataset.

Figure 11 depicts two typical examples ruled out as obvious false positives. On the left, although we detected a turn in RYR8BJ at navaid TOU, it was not a “direct-to” instruction. In this case, it is the next turn, over navaid AGN and towards MANAK, which resolves the conflict, increasing the separation with  $\min \hat{s} = 1.4$  NM and  $\min s = 7.6$  NM. On the right part of Figure 11, though the detected “direct-to” instruction over CXI33XZ was properly detected, with  $\min \hat{s} = 3.7$  NM and  $\min s = 11.7$  NM, the longer deviation, further on along the trajectory, was likely the one which resolved the conflict. This type of false positives may be easily addressed by considering only the last deviations before the CPA.

Other potential mechanisms causing false positives will be identified and addressed in subsequent research. Given our methodology based on successive thresholds, we can also expect a significant amount of false negatives. Our primary objective is to filter out irrelevant situations rather than to capture every possible deconfliction scenario.



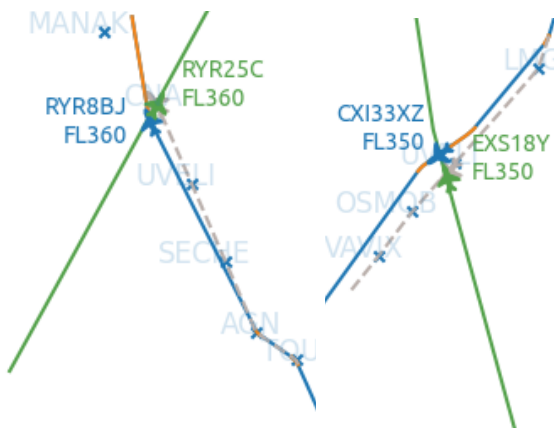


Figure 11: False positive examples, (deviated portions in orange).

This inspection of our results is only a first step towards a more comprehensive and robust validation of our method. A next step could be to ask ATC experts to validate our results, which would require to replay the resulting traffic situations. Alternatively, we might validate our method on an already labelled dataset, including ATCO’s instructions. The only publicly available labelled dataset that we know of was recently made available by the Swedish air navigation services [24].

## V. CONCLUSION

In summary, we analysed a dataset of historical ADS-B trajectories and utilized KNN-Median Regression to evaluate various indicators derived from trajectory segments not aligned with any navaid in the flight plan. The goal was to identify lateral deviations attributable to deconfliction actions taken by ATCO. By examining the median differences between actual and predicted separations across different variables (such as closest predicted separation, deviation duration, and time to the closest point of approach), we established a significant threshold of 8 NM for predicted separation. This finding aligns with an acceptable risk threshold commonly employed in the community. Being able to establish this value statistically is a strong indicator of the practical relevance of our dataset and the associated median regression method. Combining this threshold with other variables allowed us to distinguish routine turns from small deviations resulting from “direct-to” instructions. Specifically, we considered deviations lasting less than 110 seconds with a predicted separation of less than 8 NM and a time to CPA exceeding 200 seconds. In future research, we aim to refine these heuristics and to automate the extraction process further by incorporating additional explanatory variables. We also plan to validate these findings using a labelled dataset. This method could facilitate the construction of catalogues featuring deconfliction actions extracted from readily available unlabelled ADS-B data. Such catalogues could serve various purposes, including identifying common resolution strategies and modelling controller uncertainties in the resolution process. Addressing these issues is essential to ensure the acceptability of future conflict resolution tools by human operators.

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