# A Machine Learning Framework for Predicting ATC Conflict Resolution Strategies for Conformal Automation

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***Abstract*—Conformal automation allows for increased acceptability of automation tools in air traffic control. The key enabler for achieving conformity of automation tools in performing expert tasks, for example air traffic conflict resolution, is the identification of ATCO preferences (conflict resolution strategies) and its ability to learn and recommend similar strategies. This research proposes a machine learning-based framework to learn and predict the air traffic conflict resolution strategies using an ensemble model of regressor and classifier chains. This framework enables the prediction and generation of a complete conflict resolution profile of the maneuvered aircraft. Similar and contrasting ATCO conflict resolution strategies are collected through human-in-the-loop experiments, using a real-time, high fidelity simulation environment, for model training and evaluation. The prediction results demonstrate that the ATCOs strategies encoded in the collected data can be learned by the model with high accuracy (95.1%, 93.7% for choice of aircraft) and low MAE( 0.38 Nm and 0.52 Nm for maneuver initiation distance) for the ATCOs' datasets. These results demonstrate high conformance of the model predicted maneuvered trajectories with the original ATCOs maneuvers.**

## I. INTRODUCTION

The primary tasks of an ATCO are to ensure safe, orderly and efficient flow of air traffic, with safety at the highest order of precedence. In an event of a predicted loss of separation, a controller must device a strategy to resolve the conflict. A conflict resolution strategy may include several maneuvers (horizontal, vertical, speed change, or a combination of these) for ownship or intruder, and to finally merge the deviated aircraft to its originally intended flight path, as illustrated in Figure 1. While vertical maneuvers appear to be more efficient in resolving conflicts in a single maneuver without the need of subsequent monitoring, lateral maneuvers are preferred for 'strategic' conflict resolution. This is because such maneuvers cause significantly less discomfort to the passengers and do not distort the vertically stratified structure of the airspace [1].

Several automation tools are available to the ATCOs such as STCA and MTCD. However, the ATCOs seldom rely on the conflict alerts given by such tools and more on their own judgement and experience. For example, the MTCD system is rarely used by the ATCOs owing to its high false alarms and missed detects [2]. The primary reason of mistrust between ATCOs and such automation tools is the lack of conformance in how ATCOs perceive the conflict scenarios and how such automation tools provide resolution advisories.ATCOs provide safe and efficient resolutions for potential conflict scenarios. Over time, ATCOs develop some inherent preferences in managing conflicts, which can be termed as conflict resolution strategies. Automation tools that can take into consideration the ATCO strategies for conflict resolution may assist in better management of ATCOs' workload through high acceptance of such automation tools.

On this premise, this research proposes a novel machine learning-based framework and presents results from the initial experiments to predict the ATCO flight conflict resolution strategies during potential conflicts situations. The results from this initial study demonstrate that it is a viable approach to develop ATCO conformal automation tools which are capable of generating 'ATCO like' conflict resolution strategies.

## II. LITERATURE REVIEW

Approaches to develop conflict detection and resolution automation tools have evolved from using mathematical algorithms [3], modelling and optimization approaches using heuristics and constraint programming [4], to new perspectives using machine learning and deep reinforcement learning(DRL) [5], [6]. Although RL and DRL methods have gained attention in terms of their ability to better address complex decision making problems in air traffic control [7], such projects are related to fully autonomous ATCO systems and limited in using human element needed for conformity of resolution advisories by such automation aids [8]. In general, a strategy is a high-level decision-making process or the art of employing a method or a plan towards a goal [9]. Autonomous agents' strategies in games have been discussed in many benchmark papers like playing Alpha GO [10], where the agents opt for strategies that maximize the overall reward, even accepting penalties with a potential of higher delayed rewards. Within the scope of flight conflict resolution, a strategy is a high-level decision-making process to avoid a potential conflict. Strategies used by agents in such games are strikingly different from flight conflict resolution strategies where immediate rewards carry immense weight. Researchers have also defined it as a sophisticated planning skill, which is an essential element of the ATCOs' skills allowing them to handle a large amount of traffic while reserving their cognitive resources [11]. This includes decisions of aircraft maneuver choice, choice and time of maneuver direction, the extent of the deviation and where to merge the aircraft to its initial path.

Automation tools are not readily accepted by the ATCOs because of the failure to understand why automation tools

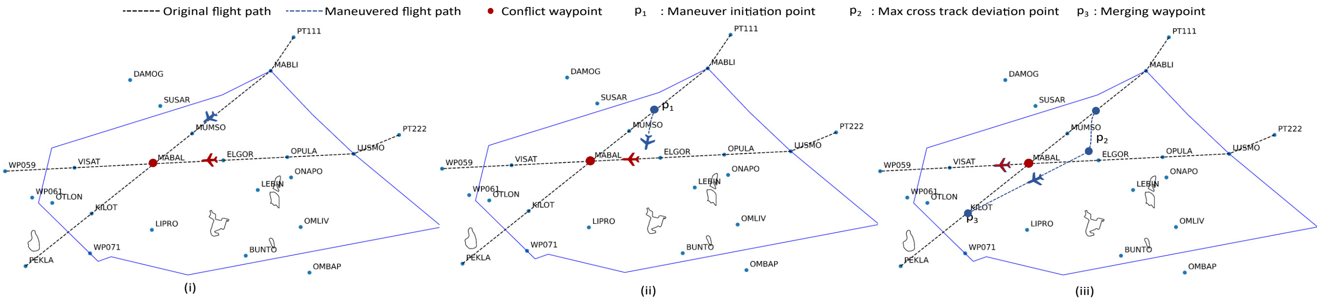



Figure 1. Conflict representation with a pair of aircraft bound to witness a loss of separation. As a conflict resolution maneuver, one aircraft initiates a maneuver at point $p_1$, is deviated to point $p_2$ and then merged into its initial path at point $p_3$. This represents the complete resolution profile of the maneuvered aircraft for this case.

propose a particular resolution. In many instances, the proposed resolution is completely different from the ATCOs' preference for a particular scenario. Hence, it is imperative to identify these inherent strategies, which the ATCOs use while resolving flight conflicts. Methods that incorporate ATCO preferences in providing solutions or provide 'ATCO like' solutions have a higher probability of acceptance and deployment for real-world applications [12]

There have been research attempts to identify strategies used by ATCOs in arrival sequencing and coping with uncertainties in air traffic control [11]. Researchers have also attempted to provide conformal automation for air traffic control by learning conflict resolution maneuvers through operator demonstrations [13]. Though this work is significant in terms of learning from ATCO demonstrations, the scenarios are standard two aircraft conflicts with conflict angles of 45°, 90° and 135°, and the ATCO can only maneuver a predecided aircraft (A/C 2). Rooijen et al. [14] used a convolutional neural network architecture (CNN) which utilized solution space diagram (SSD) images to learn the resolution maneuvers. One of the limitations of this work is that the results provide only the initial maneuver and not the complete conflict resolution profile. Also, though the authors refer to these results as 'strategies', a better interpretation here would be 'predicting the controller actions'. This is because the inherent ATCO strategies should guide the type of resolution action for a given conflict, which is the potential research gap.

The previous research efforts have majorly been to identify resolution maneuvers from historic data using different algorithms or classify the resolutions into categories. A major problem with these approaches is that historical data such as the ADS-B do not contain any potential flight conflict since ATCOs already intervene and resolve such situations. Moreover, it is difficult to identify individual ATCO strategies from the historical data. ATCOs dominantly rely on the spatial and temporal patterns of traffic rather than the instantaneous positions of the aircraft [15]. Further, most of the research is focused on tactical conflict resolution, leaving significant research prospects in the strategic component of flight conflict resolution and understanding ATCO's conflict resolution strategies.

In this research, the proposed framework consists of two key components: first, identifying ATCOs' conflict resolution strategies, and second, implementing a machine learning model to learn these strategies. To achieve this, human-in-the-loop experiments were conducted in a high-fidelity real-time simulation environment wherein the ATCOs were presented air traffic conflict scenarios. The conflict resolution maneuvers were analyzed to identify similar and contrasting conflict resolution strategies. These strategies, encoded in the data, were used as inputs to the learning model to test the generalization performance.

The document is organized as follows: Section III describes the problem formulation and the underlying assumptions. The research methodology is described in Section IV. Section V discusses the simulation environment, conflict generation and data pre-processing to extract features for the learning algorithm. This is followed by a discussion on ATCO strategies identification in section VI and machine learning algorithm details in section VII. The results and discussions are cumulated in section VIII with the conclusion and discussions in section IX.

## III. Problem Formulation

A conflict resolution strategy, S, can be mathematically represented as a ordered tuple of the governing elements, i.e, choice of aircraft (C), Maneuver initiation time (T), maneuver direction (D), cross track deviation ($D_c$) and merging waypoint (M) such that $S = (C, T, D, D_c, M)$. Each element in $S$ takes value from the feasible actions available in its domain. In particular, $C \subset \{ownship, intruder\}$, $T \subset \{T_{sim}, ...., T_{los}\}$, $D \subset \{left, right\}$, $D_c \subset \{0, ...., D_{bound}\}$, $M \subset \{\textit{list of waypoints available after } T\}$.

Here, ownship and intruder are the two aircraft in conflict, $T_{sim}$ is the current simulation time, $T_{los}$ is the simulation time at loss of separation and $D_{bound}$ is the distance of the maneuvered aircraft from sector boundary.

The complete conflict resolution strategy is captured in the collected data which is then transformed into a supervised machine learning problem as follows. Given a set of $\boldsymbol{N}$ training examples of the form $\{(X_1, Y_1), (X_2, Y_2)... , (X_m, Y_m)\}$, such that $X_i$ is the feature vector of the $i^{th}$ training example of shape $(1{\times}n)$ where $n$ represents the numbers of features and $Y_i$ is the target variable, the learning algorithm seeks a function $f$: $\boldsymbol{X} \rightarrow \boldsymbol{Y}$ which best maps $\boldsymbol{X}$ to $\boldsymbol{Y}$, where $\boldsymbol{X}$ is the input space and $\boldsymbol{Y}$ is the output space. For the $p^{th}$ model in a chained prediction sequence, the dimensions of the initial dataset $X(m{\times}n)$ changes to $X(m{\times}(n{+}p))$ as the predictions from the previous models are added to the input features for subsequent predictions.

The main assumptions for this research were:

- The conflict resolution maneuvers were restricted to the lateral direction, to isolate and enable a detailed analysis of ATCO strategies in the lateral direction.

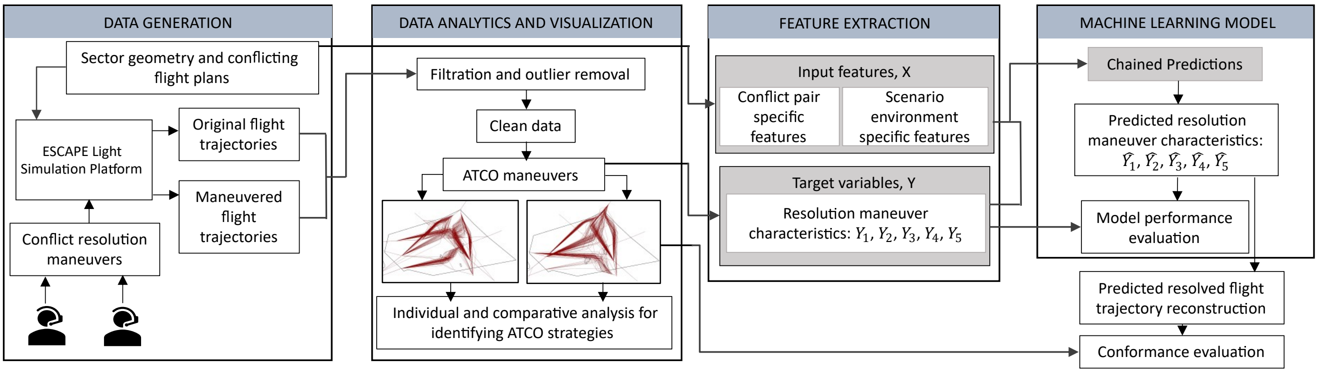



Figure 2. Four modules constituting the research framework in this study: (1) Data Generation, (2) Data analytics and visualization, (3) Feature extraction and (4) Machine learning model.

- ATCOs were instructed to resolve the primary conflict and not any subsequent conflicts arising from the initial maneuver. This is because ATCOs typically resolve conflicts in a pairwise approach [16]. In other words, when resolving conflicts, the ATCOs first look at individual conflict pairs and come up with a suitable resolution and later, check its impact on the overall traffic. It must be emphasised that though this assumption exists, the primary resolution were performed considering the surrounding traffic.

## IV. Research Methodology

The research methodology is grouped into four modules with their internal architecture, as shown in Figure 2. Module 1 consisted of generating conflict simulation data with python scripts and specifications of Sector 6 waypoints and airways, with reference to Singapore FIR. The conflict resolution maneuvers from the ATCOs were obtained on these real time conflict scenarios. Module 2 consisted of analytics, visualization and comparison of the resolved trajectories obtained from module 1. This enabled the identification of the ATCOs' conflict resolution strategies. Module 3 comprised the feature extraction process. This made use of the sector information and comparison of initial conflicting flight trajectories and the resolved flight trajectories at each time step. Module 4 used the proposed machine learning model to predict the components of the conflict resolution strategy, S, and enabled the generation of the complete conflict resolution strategy. These predicted trajectories were analyzed for conformity with original maneuvered trajectories obtained from module 2. The details of each module are presented in the following sections.

## V. Conflict simulations and data analysis

### A. Simulation environment

In order to observe the actual ATC behaviour in conflict situations, it is imperative to perform experiments in a simulation environment which replicates the ATCO radar interface. Hence, the ESCAPE Light Simulation Platform, developed by Eurocontrol, was used to capture the ATCOs' conflict resolution strategies [17].

ESCAPE Light is a high-fidelity, real-time, high-performance academic version of the ESCAPE simulator. It provides functionalities such as airspace design for en-route and TMA, flight plans input, complete flight trajectory extraction, the information of Base of Aircraft DATA, to name a few. Figure 3 shows an instance of the simulation where six aircraft are inside sector 6 and one aircraft approaching the sector. Flight GA11 has performed a heading change maneuver to avoid a potential conflict with flight QR11.

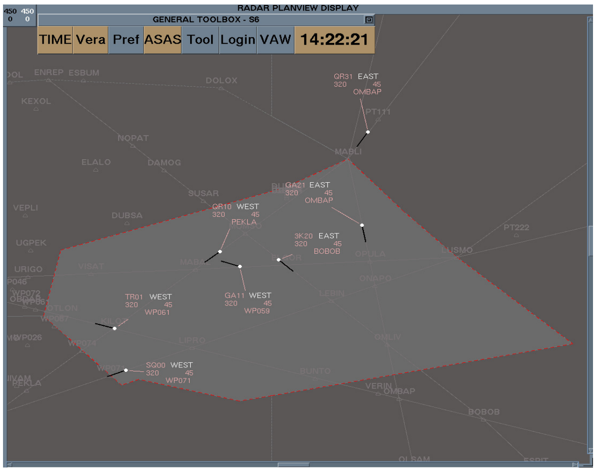



Figure 3. A snapshot of ESCAPE Light ATCO radar screen interface with Sector 6 of the Singapore FIR. It is visible that flight GA11 has performed a heading change maneuver to avoid conflict with flight QR10.

### B. Conflict scenario generation

Sector 6 of the Singapore FIR was selected to perform experiments. This is because the dynamics of Sector 6 enables detailed analysis of crossing conflicts airways as compared to other sectors and is at sufficient distance to consider en-route flight operations. Figure 4 illustrates the conflict scenario data generation process. Using Singapore FIR as a reference, the airways and conflict points in sector 6 were selected. Co-ordinate information of the sector and the waypoints were input to the simulator and pairs of conflicting flight routes were identified. Subsequently, offsets were created to ensure that the flights experience a loss of separation on these routes. The start time of every flight was perturbed by adding a randomized noise in the form of time so that though the conflict were ensured, they were not exactly the same.

### C. Data pre-processing and feature extraction

The generated flight conflict data was uploaded to the simulation environment and ATC inputs in the form of conflict resolution maneuvers were obtained. These maneuvers were stored as flight trajectories in XML format, at an interval of 5 seconds. From these trajectories, the desired parameters of time, longitude, and latitude were

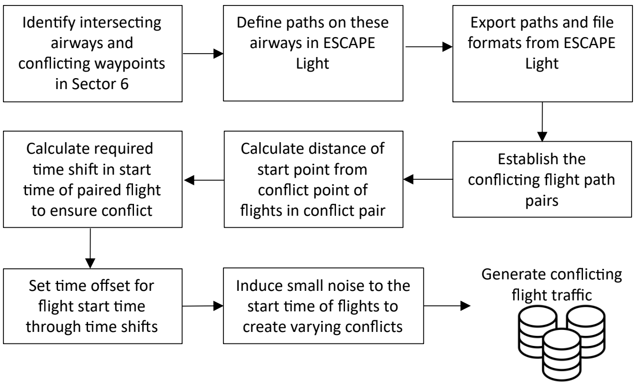



Figure 4. Conflict flight plan data generation pipeline. These flight plans were used as inputs to the simulation environment.

filtered. Further, the data was filtered to remove cases where some trajectories were not completely recorded because of simulation runtime errors.

Features representing a conflict scenario were grouped into 3 categories: (1) Conflict pair features (C.P), (2) Surrounding environment features (S.F), and (3) Resolution maneuver features (R.F). Features pertaining to conflicting flight pairs and the surrounding environment were extracted through the information of sector dimensions, airways information, and the locations of flights. For the target variables i.e the resolution maneuver features, the maneuvered flight trajectories were compared with the original flight trajectories, as shown in Figure 5. Table I shows the list of features extracted from the data and used for the learning algorithm. The abbreviations TCP, CPA, and L.O.S refer to the trajectory change point and the closest point of approach and loss of separation, respectively.

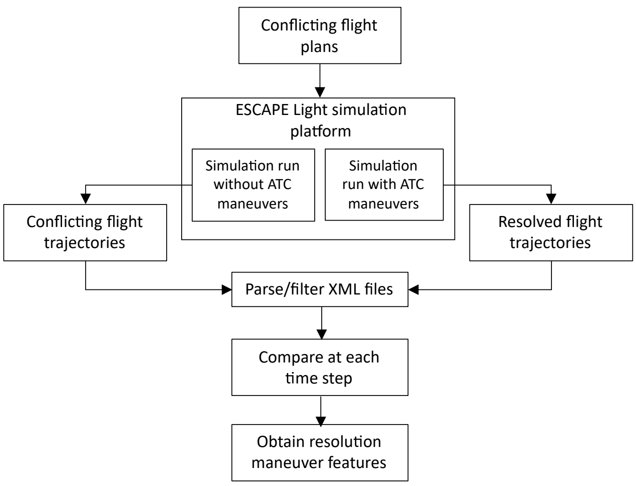



Figure 5. Comparing flight trajectories based on original flight plans with the maneuvered flight trajectories to extract conflict resolution maneuver features.

## VI. Identifying ATCOs Strategies

To identify the potential strategies, the ATCOs were presented with conflicts in the simulation environment. Aircraft appeared approximately 20 Nm outside the sector so that the ATCOs have situational awareness about the aircraft entering their sector. Both the ATCOs were presented with the same conflicts and their resolved flight trajectories were recorded by the system. The total conflict scenarios resolved by both ATCOs were 612 and 571 respectively.

TABLE I. Description of the features extracted from ATCOs' data and their abbreviations used in the figures.

| Feature name | Type | Abbreviation in figures |
|---|---|---|
| Initial heading: resolved flight | C.P | initialhead_resolved |
| Initial heading: unresolved flight | | initialhead_unresolved |
| Conflict angle | | conflict_angle |
| Distance from conflict point to maneuver start | | mantoconflict_dres |
| Distance from conflict point to the location of unresolved flight when maneuver starts | | mantoconflict_dunres |
| Direction of TCP wrt maneuvered flight | | tcp_direction |
| Direction of unresolved flight wrt TCP | | unresolvedflight_dirn |
| Distance of sector boundary from TCP | S.F | distfrombound_TCP |
| Distance of sector boundary from maneuver start | | d_bound_manstart |
| Distance of CPA of resolved flight from sector boundary | | d_bound_CPA |
| Number of neighboring aircraft | | neighbouring_ac |
| Mean distance of neighboring aircraft from the resolved aircraft at maneuver initation | | meandistance |
| Time prior to L.O.S when the resolution maneuver is initiated | R.F | timetoresolution |
| Distance prior to L.O.S when resolution maneuver is initiated | | d_resstart_CPA |
| Heading angle | | headingAngle |
| Max. cross-track deviation | | crosstrack_dist_max |
| Merging waypoint name | | mergewp_name |
| Distance between merging waypoint and TCP | | mergept_TCPdist |

C.P: Conflict pair feature; S.F: Surrounding environment feature; R.F: Resolution feature

Figure 6 shows the resolution maneuvers for ATC A (a) and ATC B (b) for the same conflict scenarios. To identify the ATCOs' strategies, these trajectories were first analyzed separately and then compared, to establish the similarities and differences between the two ATCOs' strategies.

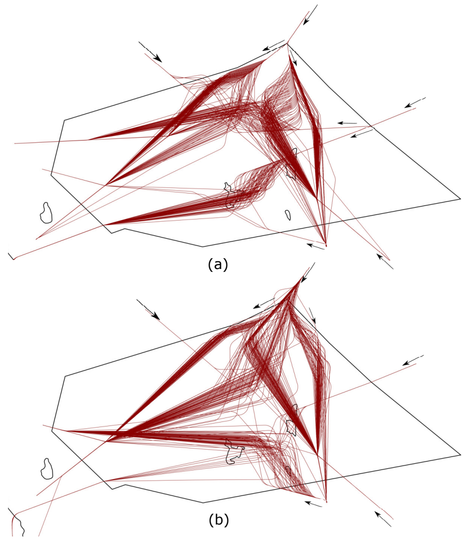



Figure 6. Resolved flight trajectories for ATC A (a) and ATC B (b)

As discussed earlier, the primary task of the ATCO are to ensure safe, orderly and efficient flow of air traffic, with safety at the highest order of precedence. Once the primary target of safety is met, different ATCOs might tweak their preferences between order and efficiency at their discretion. Only a qualitative measure of ATCO strategies can be documented when discussing the strategies in isolation. Hence, the strategies of the two ATCOs are discussed in parallel to establish quantitative measures of the identified strategies. For two of the five conflict points, the maneuvers for ATC A and ATC B are shown in Figure 7.

*1) Choice of aircraft to maneuver:* The first identified strategy was the choice of aircraft to maneuver. ATC A demonstrated a consistent strategy to choose the aircraft farther from the potential conflict point to perform a res-

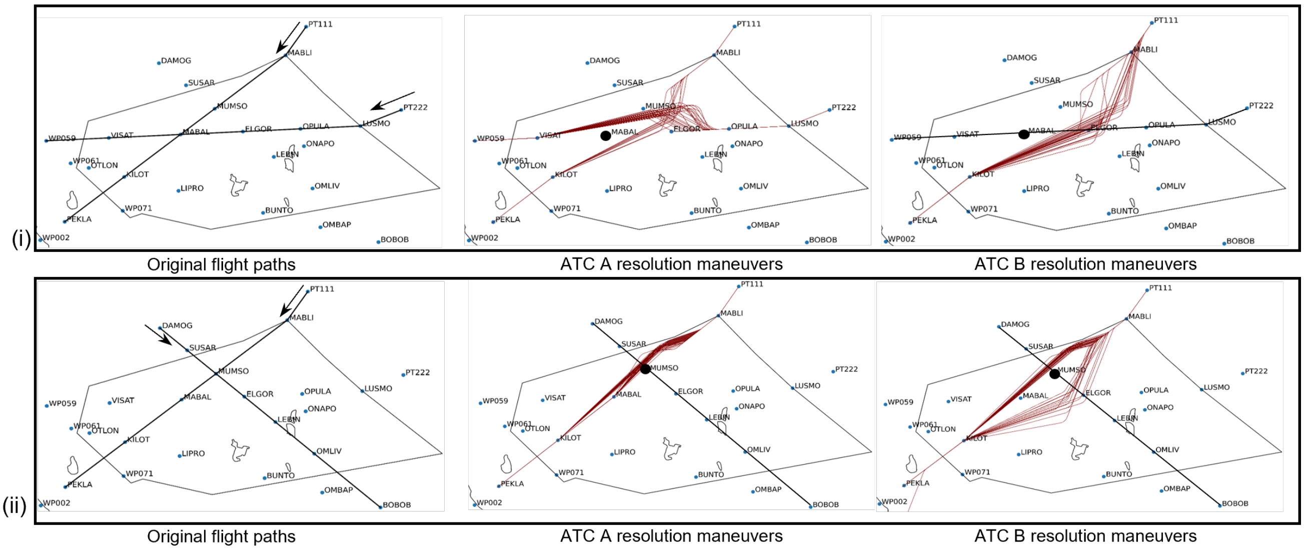



Figure 7. Resolution maneuver preference for ATC A (Column 2) and ATC B (column 3) for the five conflict points in Sector 6. The initial flight paths are shown in column 1. The conflict waypoints for corresponding airways are indicated by black markers. Out of the five conflict locations, two representative cases are shown in the figure.

olution. Out of the total 612 conflict pairs this strategy was employed for 432 cases. This is a viable strategy because providing a path stretch to the farther aircraft will always ensure the required safe separation. The cases where the nearer aircraft were chosen were the ones where it was fairly difficult to visually identify the aircraft that is nearer or farther from the conflict point. ATC B on the contrary had mixed preferences in terms of choice of the aircraft to maneuver. Out of all the conflict pairs presented to ATC B, ATC B opted for the aircraft nearer to the conflict point 323 times and maneuvered the farther aircraft 248 times. Certainly, these initial strategies have an influence on the subsequent components of the complete resolution profile.

*2) Direction of resolution maneuver:* It is evident from Figure 7 that in terms of the maneuver direction, ATC A demonstrated a consistent strategy of directing the maneuvering aircraft to the tail of the leading aircraft. In other words, the maneuvers were consistently directed within the region bound between the conflicting aircraft trajectories. This strategy complements the choice of aircraft to maneuver, as directing the farther aircraft to the tail of the nearer aircraft ensures avoiding any loss of separation. For ATC B there were two kind of strategies as are visible from figure 7. For conflict scenarios such as Figure 7, column 3:(i) the resolution strategy was similar to ATC A. In the remaining conflict configurations, it is observed that in some instances ATC B directed the aircraft away from the region bounded by the two aircraft trajectories.

*3) Maneuver initiation time (MIT):* The maneuver initiation time is the time remaining prior to the loss of separation when the resolution maneuver is initiated. Analytics of the resolved trajectories revealed that ATC A had a strategy to perform delayed maneuvers. The average MIT for all the conflict scenarios for ATC A was 6.62 minutes with only 3 resolutions between 10 to 11 minutes of MIT. On the other hand, for ATC B, the average MIT prior to a conflict was 8.7 minutes with 240 conflict scenarios with MIT greater than 10 minutes. MIT is translated to distance prior to resolution initiation to assist in better interpretation in Section VIII. It can be inferred that ATC B's strategy involved performing early maneuvers, which can be seen in Figure 8 (a) and also through visualization of maneuvers in figure 7.

*4) Cross track deviation (CTD):* The cross-track deviation is the extent to which the aircraft laterally deviates from its original flight track. The CTD for ATC A ranged between 2.64 Nm to 21.49 Nm, with an average CTD of 10.98 Nm. For ATC B the CTD values ranged between 2.71 Nm to 29.8 Nm with an average CTD of 16.07 Nm. It is clear that ATC B's conflict resolution strategy involved larger CTD, possibly to ensure that the separation standards are maintained and subsequent resolution maneuvers are not required. These deviations can also be attributed to the extent of training in a particular sector and the level of confidence of the ATCOs in the assigned maneuver.

*5) Merging distance:* Merging distance refers to the distance from point of maximum cross-track deviation to the waypoint where the deviated flight is merged to its original flight route. It depends on the choice of waypoints available to redirect the flight to its original path, keeping in mind that the maneuver is not too aggressive. From Figure 8, it is visible that the flights maneuvered by ATC B traveled a larger distance from the CTD to the merging waypoint. A key observable pattern here is the consistency of waypoint selection by the ATCOs. For instance, in Figure 7 (ii), column 3, though the ATC B had varying preferences for the maneuvering direction, the merge point for all the flights was consistently KILOT, although MABAL was available as s feasible option to ATC B in a significant number of scenarios. In contrast, ATC A merged the aircraft to any one of the available options of MABAL and KILOT. This is indicative of some visual markers that ATCOs possess to lower the airspace complexity in conflict situations with higher surrounding traffic and maintain consistency of flight route patterns in the concerned sector.

*6) Aircraft Separation achieved for resolved conflicts:* It is critically important to understand the ATCO preferences in terms of the desired separation standards. Although the mathematical or machine learning algorithms might produce resolution maneuvers that are extremely efficient, they may not be acceptable to the ATCOs due to their preferences of safety buffers. Analytics of the resolved flight trajectories revealed that both the ATCOs had similar preferences in terms of the desired separation standards, which is visible in Figure 8.(d). The average separation provided by ATC A for all conflict scenarios was 8.49 Nm and for ATC B the value was 8.82 Nm. The minor deviation was due to some extreme outliers in the case of ATC B. It is evident that both ATCOs prefer some safety buffers and in addition to the 5 Nm safety separation standard in the lateral direction. In the current case, both ATCOs have similar strategies of similar buffers while resolving conflicts.

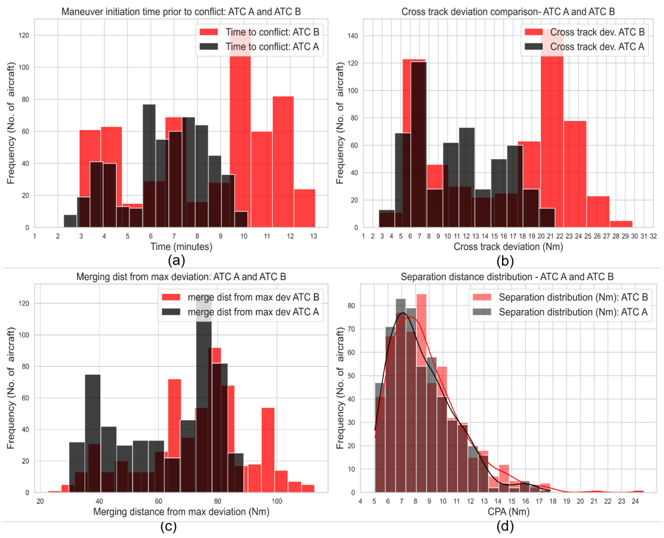



Figure 8. Comparative analysis of different phases of a resolution strategy for both ATCOs.

## VII. Learning Air Traffic Controller Strategies

### A. Machine learning model

Section VI discussed the prominent strategies which can be identified through data analytics of the controller resolution maneuvers. This section demonstrates how well a robust machine learning algorithm can generalize and learn these strategies. A very popular and robust approach is to develop an ensemble of learners such as decision trees and aggregate the predictions of these individual trees. This approach is also known as random forests. Random forests are successful in regression and classification tasks because unlike decision trees, they are less prone to over-fitting. Each tree is trained using a bootstrap sample of the training data, and at each node, the best split is selected from a random subset of the predictor variables. This ensures that each tree utilizes the training data and predictor variables in a different way, reducing its statistical dependence on the other trees. After hyperparameter tuning, the number of trees in the forest and the maximum depth were kept the same for the ATCOs' datasets, at 500 and 10. Limiting the maximum depth of each tree also prevents data overfitting.

Five random forest models were used to predict the complete resolution profile of a conflict, using the Scikit-Learn library. A complete resolution profile incorporates the following components - conflict resolution initiation time, choice of the aircraft to maneuver, issued heading, cross-track deviation, and the choice of merging waypoint. The predictions for classification or regression made by the preceding models were used as input features to the subsequent models. This methodology is also known as chained predictions. Chained predictions enable the generation a complete resolution profile for a conflict with the only drawback that the errors in the initial predictions propagate through the subsequent models as well. In hindsight, it is advantageous from the research perspective if we want to ascertain the actual accuracy for the complete resolution profile predictions. Figure 9 demonstrates the flow between the various model used for prediction.

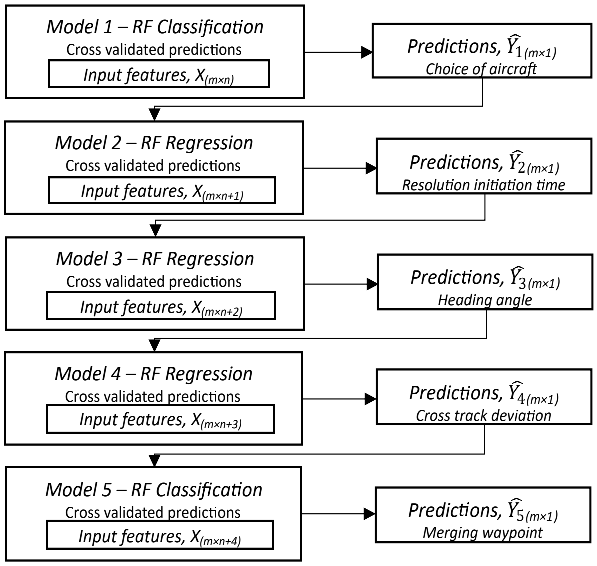



Figure 9. Multiple Random Forest models representing chained prediction sequence to predict the complete resolution profile for flight conflicts.

### B. Model performance evaluation

The generalization performance of the models for both the datasets was measured in terms of classification accuracy and mean absolute error (MAE).These error values are an indicator to how well the model is able to learn and generalize the strategies of the ATCOs, which have been captured in the resolution maneuvers provided by them. If $\hat{y}_i$ is the predicted value of the $i^{th}$ sample and $y_i$ is the corresponding true value, then the classification accuracy over $n_{samples}$ is defined as:

$$Accuracy(y,\hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} (y_i = \hat{y}_i)$$

Similarly, if $\hat{y}_i$ is the predicted value of the $i^{th}$ sample and $y_i$ is the corresponding true value, then the the mean absolute error over $n_{samples}$ is defined as:

$$MAE(y,\hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} |(y_i - \hat{y}_i)|$$

For the current datasets, 5-fold cross validation was used in the experiments.

## VIII. Results

### A. Prediction results

Table II shows the performance metrics for the different random forest classification and regression models used in the prediction task. These results demonstrate that chained prediction can deliver close estimates of the strategies obtained from ATCOs' datasets. The classification accuracy

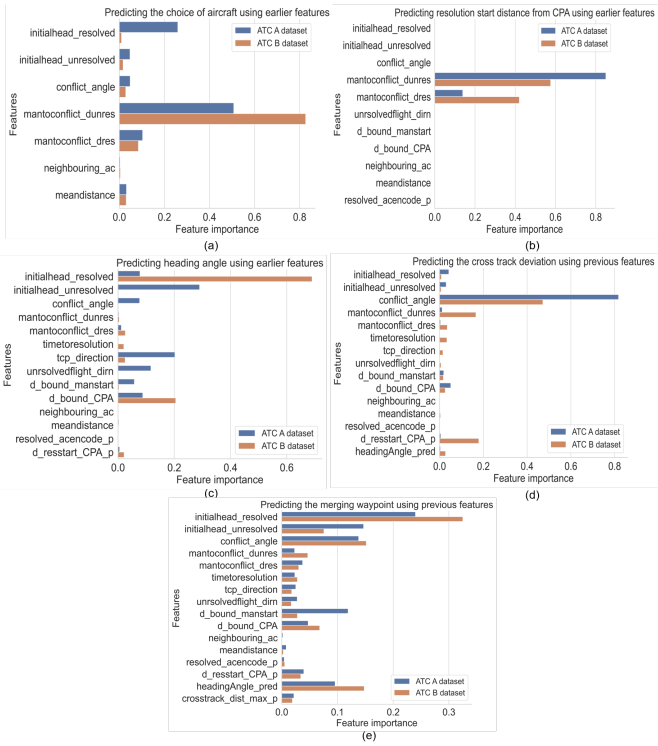



Figure 10. Feature importance values for the random forest models for the two ATCOs. 'resolved_acencode_p', 'd_resstart_CPA_p', 'headingangle_pred' and 'crosstrack_dist_max_p' represent the predicted values by the random forest models.

for the choice of aircraft to maneuver was 95.1% and 93.7% for ATC A and ATC B, respectively. Most misclassified cases involved scenarios where both the aircraft of the conflict pair were approximately at the same distance from the conflict point. This indicates that the performance drops in situations where ATCOs demonstrate a random selection of aircraft to maneuver. Similarly, the classification accuracy for ATC A's dataset in predicting the merging waypoint was lower potentially due to the usage of both MABAL and KILOT as merging waypoints randomly, because both were feasible options as shown in Figure 7.(ii). This also highlights the challenges to the generalization approach using supervised learning algorithms. For the other models, the mean absolute error values are fairly small.

Figure 10 delineates crucial information about the features used by the corresponding models to make predictions. It can be seen that for different prediction tasks for both ATCOs' datasets, feature importance values differ significantly. For example, to predict the heading angle from ATC A's dataset, the initial heading of both the aircraft, conflict angle, direction of the unresolved flight are the dominant features. On the other hand, for ATC B's dataset, only the initial heading of the resolved flight and the distance of CPA from sector boundary are considered important. Similarly, in order to predict the cross-track deviation using the available features, (Figure10, d) the conflict angle is the most important feature for ATC A's dataset, but for ATC B's dataset, multiple other features also play a role. Since the ATCOs' strategies are encoded in the collected conflict resolution data, this is a potential indicator of the features that the two ATCs dominantly consider important while making decisions for each case. It is also evident that to predict the last component (merging waypoint) of the complete resolution profile, all the predicted components of the resolution maneuver, i.e choice of maneuvered aircraft, the distance of maneuver initiation from the CPA, heading angle, and the cross-track deviation, are important (Figure 10.(e). which highlights the importance of using chained prediction models.

The performance of Random forests, XGBoost, and Support vector machines (SVM) was compared to indicate the performance measures for tree-based and kernel-based models (Table II). For tree-based models, random forests and XGBoost have almost similar performance and the differences are not significant. XGBoost has better performance in predicting the choice of aircraft to maneuver for the dataset obtained from ATC B. SVM with an RBF (radial bias function) kernel has a slightly lower performance than random forest and XGBoost for most of the models, specifically for prediction maneuvered aircraft choice.

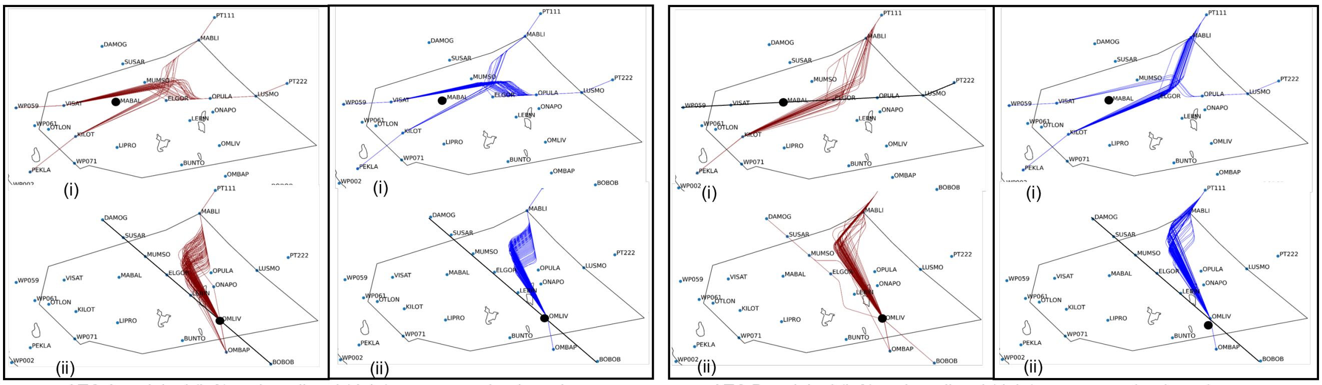
TABLE II. Performance comparison for the selected models. The best performance values are in bold.

| | Model Performance (ATC A, ATC B) | | |
|---|---|---|---|
| Metric | R.F | XGBoost | SVM |
| Classification accuracy, % (Choice of aircraft) | **95.1**, 93.7 | 95.01, **95.07** | 92.45, 92.8 |
| MAE, Nm (Maneuver initiation distance ) | **0.38**, 0.52 | 0.47, **0.45** | 0.77, 1.39 |
| MAE, Nm (Heading angle) | 5.15, **3.66** | 5.36, **3.15** | 5.70, 5.55 |
| MAE, Nm (Cross track deviation) | **1.18**, 1.63 | 1.29, 1.69 | 1.24, **1.59** |
| classification accuracy, % (Merging waypoint) | **93.6**, **99.2** | 92.09, 98.8 | 93.3, 98.8 |

Using the predicted values of the components of the strategy tuple, S, complete predicted trajectories can be recreated as shown in Figure 11. These predicted trajectories are generated for the scenarios where the first prediction i.e. the choice of aircraft is correct. It is visible that the predicted trajectories closely conform to the actual maneuvered trajectories shown in Figure 6, which in addition ascertains that the chained prediction model can generalize the actual resolution preferences of the ATCOs. For example, for the strategy tuple $S = (SQ160,\ 6.26\ minutes,\ Left,\ 14.82\ Nm,\ WP071)$, obtained from ATC A, the predicted strategy tuple is $\hat{S} = (SQ160,\ 6.19\ minutes,\ Left,\ 12.32\ Nm,\ WP071)$.

## IX. Discussions and Conclusion

The framework proposed in this paper is a viable approach to identify and learn the ATCO conflict resolution strategies for conformal automation. The analysis in section VI provides key insights and highlights the strategies used by both the ATCOs on the same conflicts, with situations where they demonstrated similar and contrasting strategies for conflict resolution. For the majority of the scenarios, ATC A prefers delayed resolutions, with maneuvers by the trailing aircraft towards the tail of the leading aircraft. The cross-track deviations and merging distances were less when compared to ATC B. ATC B's strategies included early maneuvers with a mix of preferred aircraft to maneuver and maneuver directions, with larger values of cross-track deviation and merging distance. The prediction performance through chained predictions shows high conformance with the original resolution profiles. In this work, cross-validation was used to estimate the generalization error of the machine



ATC A : original (left) and predicted (right) maneuvered trajectories

ATC B : original (left) and predicted (right) maneuvered trajectories

Figure 11. A comparison of the original resolutions and the resolved trajectories generated through chained predictions for ATC A and ATC B. Close conformance of the predicted trajectories with the original maneuvered trajectories is evident from these images. Here, only two of the five conflict points have been shown.

learning model. This is because the available dataset is too small and the test set taken from it might not be a good representative of the entire dataset. This may lead to high variance over multiple runs of the model [18]. Although this is the case, a limitation of this work is the use of the same conflict configurations to test for conformance. With the current methodology, it is difficult to explain the scenarios where the choice of aircraft is wrongly predicted. Although, the predictions error in this situation can be accredited to the random selection by the ATCOs and the inability of the supervised learning algorithms to identify patterns in such situations, addressing this is proposed as an extension to the current research. There is also a need to upscale these initial experiments to include more controllers and complex traffic scenarios, which will provide insights if there are other strategies and conflict resolution patterns which exist. Also, the effect of factors such as weather and traffic density on these strategies is worth exploring.

Developing autonomous systems which incorporate ATCO behaviors in air traffic control is important for the systems to be acceptable in the operational environment. Such systems have potential usage as advisory tools to alleviate ATCO workload in conflict scenarios. On this premise, the proposed framework can identify the strategies that the ATCOs use while resolving conflict and predict and generate the complete conflict resolution profiles for the given conflict scenario. The predicted trajectories were shown to have close conformance with the original maneuvers provided by the ATCOs and the prediction model was able to learn and generalize the strategies significantly well.

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