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MODELLING AIRCRAFT PRIORITY ASSIGNMENT BY AIR TRAFFIC CONTROLLERS DURING TAXIING CONFLICTS USING MACHINE LEARNING

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ABSTRACT

Conflicts between taxiing aircraft are resolved by making the aircraft with lower priority wait, slow down, or change their path. Prevalent priority assignment is based on rules such as First Come First Serve. However, this is not viable as priority assignment done by an air-traffic controller (ATC) based on multiple factors. Thus, a machine learning approach is proposed to mimic an ATC's priority assignment. Firstly, the potential conflict scenarios between two aircraft from historical data, which are resolved, are detected and extracted. Then a Random Forest model is developed to learn ATC's behaviors. The model mimics ATC's behavior with an accuracy of 89% and can thus be an effective approach for priority assignment in path-planning and conflict resolution. Further analysis indicates that features such as unimpeded time difference, distance to destination and start, and speed are major considerations that affect the ATC's decisions.

1 INTRODUCTION

The overall air traveler count is expected to reach 4 billion by 2024, as forecasted by the International Air Transport Association (IATA 2022). Consequently, numerous airports are constructing new terminals and expanding runways. This expansion is increasing the structural complexity of airports, thus intensifying taxiing congestion and reducing operational efficiency. Its economic consequences are severe, with approximately $33 billion lost annually due to flight delays in the U.S alone, according to the Federal Aviation Administration (FAA 2022).

Besides, efficiently using existing airport capacity is also important to handle more passengers. Several novel concepts and systems for airport surface management have been developed and implemented to improve the aircraft taxiing efficiency. In which, the idea of using autonomous vehicles to tow aircraft from the gate to the runway and vice versa is considered as one of the promising solutions (Battipede et al. 2010). Dynamic path scheduling and conflict resolution, which require aircraft priority assignment, are at the core of such solution since autonomous vehicles must be able to efficiently adjust their paths in real-time to avoid conflicts. Dynamic path scheduling systems typically involve minimizing the taxi time while satisfying the conflict avoidance constraints. Conflict avoidance systems consist of two phases: conflict detection and conflict resolution. In the detection phase, aircraft trajectories are forecasted to identify possible conflicts. In the resolution phase, the aircraft with lower priority is made to slow down, wait or change its path. However, the assignment of priority is usually based on simple rules such as First Come First Serve (FCFS). These rules can significantly change the results of conflict resolution algorithms, thereby affecting the operational efficiency and throughput of the airport. Here, this study proposes a robust

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learning approach to determine which aircraft should get higher priority during taxiing conflict resolution. This is done by identifying interventions by the ATC that prevented conflict occurrence and then leveraging machine learning to mimic this decision-making when potential conflicts are detected.

2 RELATED WORK AND MOTIVATION

To maximize the operational efficiencies of the airport, extensive research has been done in the area of aircraft path scheduling and conflict resolution for aircraft ground movement. The most typical objective function in taxiway optimization is to reduce total taxi time. Pesic et al. (2001) used a genetic algorithm to minimise taxiing time, but they define conflicts as only when the gap between two aircraft is lesser than a minimum distance. A real-time airport ground movement planning method is proposed by Evertse and Visser (2017) which provides conflict-free paths for aircraft while reducing overall pollution, fuel consumption, departure slot time deviations, and taxi time. Zhang et al. (2018) used linear programming and particle swarm optimisation to generate accurate velocity profiles that ensure conflict-free movement that is fuel-efficient and respects timing constraints. Complex network theory is used by Landry et al. (2013) to dynamically perform conflict detection and resolution. Podgórski and Skorupski (2016) created a dynamic taxi route choice model which uses conflict points during congestion to calculate alternate taxiing routes. Zhou and Jiang (2015) integrate conflict resolution into path planning by first initialising paths using an improved A* algorithm and then performing conflict detection and resolution. In the event of a conflict, an aircraft either waits or changes its path based on what minimises the total cost of a heuristic function.

Path scheduling algorithms based on conflict detection operate by first initialising each aircraft's path as the shortest one from its start to its destination and then subsequently detecting the conflicts that would occur and resolving them one by one. For each conflict detected, aircraft priority is needed to determine which of the conflicting aircraft will have to alter its route from its ideal path or slow down. Real-time conflict resolution algorithms also need aircraft priority for the same reason. In the past, this priority assignment has largely been derived from assumptions or subjective rules. The work by Zhao et al. (2021) is one such example that uses the FCFS approach. Zhou and Jiang (2015) follow the priority principle that a departure aircraft is given priority over an arrival aircraft, and a larger aircraft is given priority over smaller aircraft. The priority assignment of aircraft can have a heavy impact on the efficiency of airport operations as illustrated by Jiang et al. (2020) who reduced the total waiting time by 50% and running time by 43.6 seconds by taking the aircraft priority into account during conflict resolution as compared to a common conflict resolution strategy (FCFS and aircraft can only avoid conflicts by waiting). Their priority assignment method, even though more sophisticated, was still based on rules regarding aircraft characteristics. Nevertheless, it is clear that a learning approach for priority assignment during conflicts can further optimize aircraft taxiing. Furthermore, such approach will contribute to an autonomous airport air-side environment which will be managed by tractor bots. In such an environment, there will be no intermediate holding points, and the aircraft will be able to have unimpeded taxiing motion in which all conflicts will be resolved by taking aircraft priority into consideration.

3 METHODOLOGY

The idea underlying this research is that if a model can identify situations in which an ATC intervened to prevent a conflict by ordering an aircraft to slow down, the features of the conflicting aircraft can be utilized to understand how the ATC made the priority assignment decision. To accomplish this, firstly, those instances are identified where an ATC deliberately made an aircraft slow down to avoid a potential conflict. Secondly, those timestamps at which the aircraft enters and exits each node and edge are computed such that if it had not slowed down but rather continued at the average speed profile. Thirdly, a taxiway conflict detection algorithm is used on these computed timestamps to determine those conflicts that were prevented due to the ATC intervention. This provides a set of conflicts between aircraft and the corresponding decision made by the ATC on which aircraft to slow down to prevent the conflict. Fourthly, features are extracted from the avoided conflicts and a random forest model is used to learn the ATC's decision-making. During this step, it is assumed that an ATC requires 2 minutes to decide the priority assignment, and thus all features are extracted at a timestamp that is 2 minutes before the ATC intervention (this assumption is based on an interview with an existing ATC). Lastly, the relationship between the features and the outcome is interpreted to gain insights into the ATC's decision-making. The flowchart of the proposed method is depicted in Figure 1.

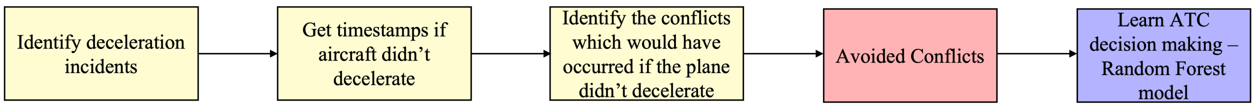


Figure 1: Flowchart of the proposed method.

3.1 Taxiway Conflict Conditions

Aircraft taxiway conflicts can be divided into three categories (Figure 2) - intersection conflicts, head-on conflicts, and rear-end conflicts (Zhou and Jiang 2015; Zhao et al. 2021). Each conflict involves a pair of aircraft which, from this point onwards, are referred as aircraft 1 and aircraft 2 based on their time to the conflict point or segment. The conditions that cause each of these conflicts are discussed in sections 3.1.1 - 3.1.3.

3.1.1 Intersection Conflict

An intersection conflict occurs when multiple aircraft pass through the same junction (or intersection) within a time interval lesser than the safety limit. The timestamps at which each flight crosses a node is used to detect this conflict. Consider two aircraft crossing a node A at times t_1 and t_2. The minimum time of separation is S. Then, the condition for an intersection conflict to occur is $|t_1 - t_2| < S$. This scenario is illustrated by the space-time diagram in Figure 3a.

3.1.2 Head-on Conflict

A head-on conflict occurs when two aircraft are approaching each other on the same taxiway in opposite directions with no exit between them. The time each flight enters and exits an edge can be monitored to detect this conflict. Consider two aircraft entering an edge AB. Aircraft 1 has a direction from A to B, while aircraft 2 has a direction from B to A. Let t_1^{in} and t_2^{in} be the time aircraft 1 and aircraft 2 enter the edge and t_1^{out} be the time they exit the edge respectively where aircraft 1 enters the edge first. Then, for a head-on conflict to occur:

$$\begin{cases} \text{aircraft}_1 \text{ and aircraft}_2 \text{ are in opposite directions} \\ t_1^{\text{in}} < t_2^{\text{in}} \text{ aircraft}_1 \text{ enters the edge first} \\ t_2^{\text{in}} < t_1^{\text{out}} \text{ aircraft}_2 \text{ enters the edge before aircraft 1 exits} \end{cases}$$

Figure 3b shows this conflict condition in a space-time diagram where the overlapping region represents the conflict interval.

3.1.3 Rear-end Conflict

A rear-end conflict occurs when two aircraft are taxiing in the same direction, but the distance between them is less than the minimum safety threshold. The minimum safety threshold chosen in our work is based on aircraft size and can be found in Table 1 (Zhao et al. 2021).

Table 1: Minimum separation between taxiing aircraft.

Leading Aircraft	Trailing Aircraft		
	Light	Medium	Heavy
Light	100m	100m	100m
Medium	200m	200m	200m
Heavy	300m	300m	300m

To detect rear-end conflicts, the in and out time of the aircraft at each edge is used. For this conflict, two aircraft must be on the same edge at the same time and be moving in the same direction. If the aircraft behind is faster, the gap between the aircraft continuously reduces. If the gap between these aircraft falls below a safe separation distance, a rear-end conflict is detected. This is monitored by checking if the final gap between the aircraft when the front aircraft exits is lesser than the threshold value. Consider two aircraft taxiing along an edge AB in the same direction. Let t_1^{in} and t_2^{in} be the time aircraft 1 and aircraft 2 enter the edge and t_1^{out} and t_2^{out} be the time they exit the edge respectively where aircraft 1 enters the edge first. Let the taxiing speed of the aircraft be V_1 and V_2. Let the initial gap be the distance between the aircraft when aircraft 2 enters the edge given by Equation 1. Let the final gap be the distance between the aircraft when aircraft 1 leaves the edge given by Equation 2. Let the minimum safety distance between the aircraft be SD.

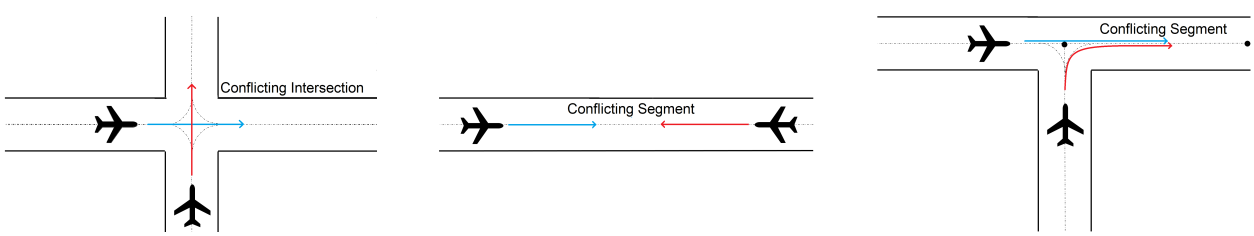
$$\text{initial gap} = V_1(t_2^{\text{in}} - t_1^{\text{in}}) \tag{1}$$

$$\text{final gap} = \text{initial gap} - (V_2 - V_1)(t_1^{\text{out}} - t_2^{\text{in}}) \tag{2}$$

Then, for a rear-end conflict to occur:

$$\begin{cases} \text{aircraft}_1 \text{ and aircraft}_2 \text{ are in the same direction} \\ t_1^{\text{in}} < t_2^{\text{in}} \text{ aircraft}_1 \text{ enters edge first} \\ V_2 > V_1 \text{ aircraft}_2 \text{ is faster} \\ \text{final gap} < SD \text{ final gap lesser than the safe distance} \end{cases}$$

Figure 3c shows this conflict condition in a space-time diagram.

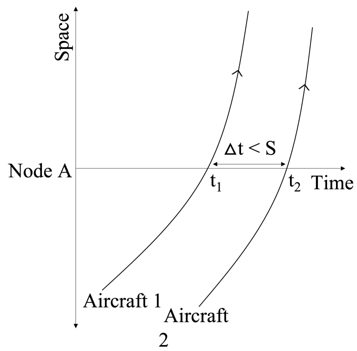


(a) Intersection conflict. (b) Head-on conflict. (c) Rear-end conflict.

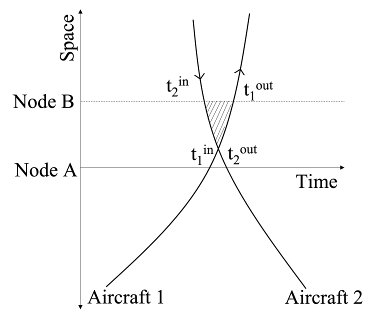
Figure 2: Visualization for 3 aircraft taxiway conflict types.

3.2 Avoided Conflicts Detection

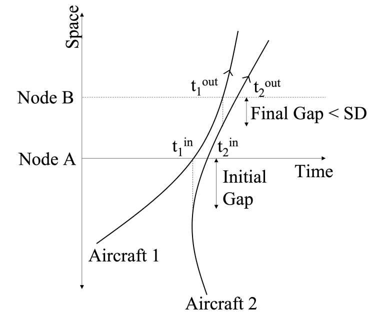
Avoided conflicts refer to those conflicts that could have occurred but were avoided due to an intervention by the ATC. It is assumed that if at any point in time, an aircraft's average speed for the next ten seconds is lesser than its current speed by 80% or more, along with a minimum reduction of 1m/s, an intervention by the ATC has taken place to instruct the aircraft to slow down. This is due to the research's hypothesis that



(a) Intersection conflict.



(b) Head-on conflict.



(c) Rear-end conflict.

Figure 3: Space-time diagram.

this unexpected decrease in speed would not occur during normal taxiing action. An example of the speed profile corresponding to one deceleration incident identified in the data is shown in Figure 4. With these deceleration instances identified, those timestamps of the aircraft for each node and edge are calculated that would exist if the aircraft had not slowed down but rather continued with the average speed of aircraft of that size at every edge. The conflict detection algorithm is then run with the updated timestamps of this aircraft to identify the avoided conflicts.

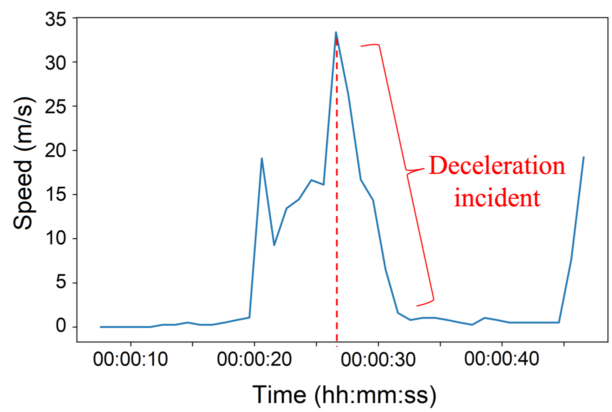


Figure 4: Speed profile corresponding to deceleration incident detected from the data.

3.3 Data Pre-processing

3.3.1 Data Cleaning

The data cleaning procedure in this study consists of three steps: correcting errors brought on by map-matching, avoiding data duplication, and filtering out relevant rear-end conflicts. Errors in map-matching are accounted for by removing an avoided conflict if any of the aircraft were on an apron at the time of conflict and were incorrectly matched to be on the taxiway. Additionally, those instances where the ‘in time’ and ‘out time’ of a flight in an edge is found to be the same due to insufficient data, are dropped. Duplication of data would result from a deceleration incident that caused many conflicts between the same pair of flights along their path. Therefore, if this scenario occurs, only the first prevented confrontations between the planes are taken into account. Additionally, since every deceleration incident takes the speed of the next ten seconds into account, the minimum time difference between avoided conflicts caused by the same deceleration incident of the same flight must be greater than this interval. Last but not least, rear-end collisions must be filtered out in the event that two aircraft approach the edge in the same path. Intuitively, we know if a rear-end conflict occurs, then the ATC will always choose to make the aircraft behind slow down. If a rear-end conflict occurs at an edge, then there are two possibilities: 1) the aircraft enter the edge following the same path, or 2) the aircraft enter the edge following different paths (Figure 2c). In the first case, an ATC has no influence on which aircraft will be ahead as they are already following the same path. Therefore, if this is the case when the ATC makes his decision on which aircraft to give higher priority, the data points are dropped as aircraft characteristics are irrelevant to the decision. However, in the second case, the ATC directly chooses which aircraft will be given higher priority based on its features, and thus, these points are relevant to our analysis.

3.3.2 Feature Extraction

For every avoided conflict between two aircraft, several features are extracted regarding the state of the aircraft 2 minutes before the corresponding deceleration incident that may be relevant to the decision of which flight should decelerate. The reasoning behind this interval is that we assume an ATC instructs an aircraft to decelerate 2 minutes before it begins to do so. The feature vectors are then input to the machine learning model for prediction. The features used are as follows :

- **Speed of aircraft**: The hypothesis here is that a faster aircraft is more likely to be instructed to decelerate when compared to a slower one. The speed in meters per second is indicated by variables 'speed1' and 'speed2', respectively.
- **Type of Aircraft**: An aircraft can be of two types: Arrival and Departure. The hypothesis here is that a departure aircraft may be given priority over an arrival aircraft as it has a much stricter schedule to attend to. The aircraft type is indicated by the binary variables 'departure1' and 'departure2' respectively where 1 means departure and 0 means arrival.
- **Size of Aircraft**: An aircraft can be of sizes: Heavy (H), Medium (M), or Light (L). Our data consists of only heavy and medium aircraft. The hypothesis here is that a heavy aircraft may have higher priority than a medium aircraft as it is likely to have a larger number of passengers. The size of the aircraft is indicated by binary variables 'H1' and 'H2' respectively where 1 means heavy and 0 means medium.
- **Distance from Start**: This is the actual distance along the taxiway traveled by the aircraft from the start to their position 2 minutes before the deceleration incident. An aircraft closer to its start may be given lower priority than one that is further away. For an arrival aircraft, its start is its landing point and for a departure aircraft, its start is its parking space. The distance from the start is indicated by variables 'dist_from_start' and 'dist_from_start2', respectively.
- **Distance to End**: This is the actual distance along the taxiway that an aircraft needs to travel to reach its destination if its path is unchanged. The hypothesis here is that an aircraft closer to its destination may be given higher priority so that it can complete taxiing. For an arrival aircraft, its end is its parking space and for a departure aircraft, its end is its take-off point. The distance to end is indicated by variables 'dist_to_end1' and 'dist_to_end2', respectively.
- **Unimpeded Time Difference**: Unimpeded time is the time an aircraft would take to reach its destination if it follows the average speed profile of each edge. The difference between the scheduled time (the time at which the aircraft will reach its destination based on its assigned path and speed profile) for an aircraft to reach its destination and its unimpeded time is calculated to get the 'unimpeded time difference'. The hypothesis here is that a higher priority aircraft would have a scheduled time closer to or before its unimpeded time (negative unimpeded time difference) whereas a lower priority aircraft will have its scheduled time higher than its unimpeded time (positive unimpeded time difference). For this work, the actual time at which the aircraft reaches its destination is considered the scheduled time. Thus, for an arrival aircraft, the scheduled time is the actual taxi-in time and unimpeded time is the unimpeded taxi-in time while for a departure aircraft, the scheduled

time is the actual taxi-out time and unimpeded time is the unimpeded taxi-out time. The unimpeded time difference, which is calculated by subtracting the scheduled time from the unhindered time, is represented by the variables 'unimpeded_time_diff1' and 'unimpeded_time_diff2', respectively.

- **Hour of the day**: Certain characteristics may be more dominant at different times of the day. For example, heavy aircraft may be given priority in the nighttime as many overseas flights are scheduled for then. The hour of the day is indicated by the variable 'hour'.
- **Conflict Type**: The conflict type may change the importance of features needed to decide on which aircraft to decelerate. The conflict type is indicated by binary variables 'intersection_conflict', 'head_on_conflict', and 'rear_end_conflict'.
- **priority_assignment**: A binary variable that tells which aircraft gets lower priority and is instructed to slow down to avoid conflict. 1 means that flight 1 is given lower priority and 0 means that flight 2 is given lower priority. This is the target variable of the model.

It must be noted that the decision of which aircraft is made aircraft 1 and which is made aircraft 2 is random and does not affect the model as the corresponding features are updated accordingly.

3.4 Model Selection

A Random Forest model consists of a combination of decision trees where each tree, recursively performs binary splits of the data based on a condition until it reaches homogenous nodes (where data belongs to only one class) or near-homogenous nodes. At each step, the condition for the split is based on that which gives the maximum information gain thereby improving the homogeneity of the data splits (nodes). As each tree uses a different subset of the training data and a different subset of features, the trees are de-correlated which leads to better generalization and low variance. This makes the model better at dealing with noise which is important for our problem as we only consider a set of features based on the aircraft's location and speed when in reality, there may be many factors such as the fuel consumption and aircraft condition that may influence the ATC's decision on which aircraft to give higher priority during conflicts and have not been considered in our feature set. Additionally, the Random Forest is easy to implement and can reduce overfitting without substantially affecting the prediction accuracy (Zhou et al. 2020). Furthermore, methods such as SHapley Additive exPlanation (SHAP) (Lundberg and Lee 2017) allow us to effectively interpret the model and thus gain insights into how each factor affects the ATC's decision when determining which aircraft to slow down in case of a potential conflict. Thus, the random forest model is selected for our analysis.

4 EXPERIMENTS

This work uses A-SMGCS data from the Singapore Changi Airport for the period 1st October 2017 to 14th October 2017. The data provides information regarding the characteristics and movement of 9824 flights. The position and velocity of the aircraft in intervals of roughly one second are available in cartesian coordinates and WGS-84 coordinates. To make this data suitable for analysis, all the aircraft trajectories are mapped onto a geometric network using the map-matching methodology proposed by Tran, Pham, and Alam (2020). Then, the avoided conflicts are detected and divided into a train and test set for machine learning. The train set comprises avoided conflicts data from 1st October 2017 to 7th October 2017 which results in 1286 instances in total after all pre-processing. The test set comprises avoided conflicts data from 8th October 2017 to 14th October 2017 which results in 660 instances in total after all pre-processing. The frequencies of the avoided conflicts detected based on the type of conflict is shown in Table 2a.

5 RESULTS AND DISCUSSION

5.1 Priority Assignment

The model for trained using avoided conflicts data from 1st October 2017 to 7th October 2017 to learn how the ATC assigned the priority and tested on avoided conflicts data from 8th October 2017 to 14th October 2017 (refer to Table 2a). The purpose of training using data from one week and testing using data from another week is to challenge the model and determine if the model has learned from the data. The model achieved an overall accuracy of 88.9% and an out of bag score of 92.5% (refer to Table 2b). This suggests that the model can accurately learn from the data and predict which aircraft will be chosen by the ATC to decelerate i.e. given lower priority. High precision and recall with a corresponding weighted average F1 score and macro average F1 score of 89% indicate that there is no bias in the prediction (refer to Table 3).

Table 2: The extracted conflict data and the overall performance of the proposed model.

(a) The total detected avoided conflicts from 1st October 2017 to 14th October 2017.

Conflict type	No. of Occurrences
Intersection	219
Head-on	50
Rear-end	1677

(b) The priority-assignment results of the trained Random Forest model.

Accuracy	88.9%
Macro Average F1 Score	89%
Weighted Average F1 Score	89%
Out of Bag Score	92.5%

Table 3: Results of each class.

Priority-assignment class	Precision	Recall	F1 Score	Support
Prioritizing Aircraft 1	89%	89%	89%	328
Prioritizing Aircraft 2	89%	89%	89%	332

5.2 Feature Importance

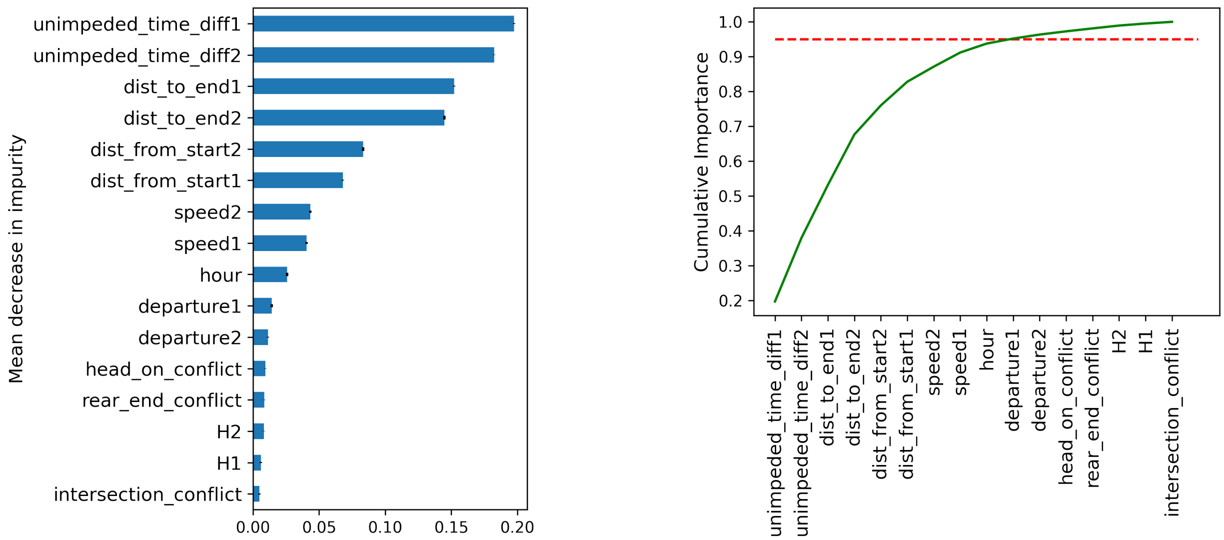
By studying the relative importance of the features, we can understand the contribution of each feature to the ATC's decision-making. Then, we use the SHAP method to interpret the relationship of each variable with the outcome. By observing the individual SHAP values of each feature, we get an insight into how changes in the feature's value affect the priority assignment by the ATC. The distinct advantage of this procedure is that the thresholds for different features and how they affect the ATC's decision are arbitrary in traditional rule-based systems while our approach learns from the data to identify the patterns in how the ATC assigns priority.

5.2.1 Relative Importance

The relative importance of the features is evaluated using the mean decrease in impurity (MDI). As illustrated in Figure 5a, unimpeded time difference, distance from end, distance from start, speed, and hour are found to be the dominating features. These features together have a 95% impact on the model outcome, as illustrated in Figure 5b. The size of aircraft, type of aircraft, and conflict type does not contribute majorly to the decision.

5.2.2 Individual Feature Importance

The SHAP module is used to study how changes in the value of the features affect the decision made by the model. These results are depicted in Figure 6 with the features with higher importance at the top based



(a) Feature importance using MDI. (b) Cumulative importance.

Figure 5: Feature importance.

on the SHAP method. In the analysis, the positive class is defined as when flight1 is chosen to decelerate (or given lower priority). Therefore, a negative SHAP value of a feature value means that it is negatively impacting the decision that flight 1 will decelerate and be given lower priority. A positive SHAP value of a feature means that it makes it more likely for flight 1 to be the one to decelerate. The impact of each significant factor are discussed below.

Unimpeded time difference: As expected, a negative unimpeded time indicates higher priority and makes it less likely for an aircraft to be chosen to decelerate. This is seen in Figure 7a and Figure 8a in the trend of both aircraft 1 and 2. A negative value of aircraft 2's unimpeded time difference makes it more likely for aircraft 1 to be chosen to decelerate (given lower priority). The individual SHAP values of the unimpeded time difference of both aircraft support this analogy (refer Figure 7a-8a).

Distance of aircraft from their ending and starting point: Intuitively, it would be practical for an aircraft very close to its end to not stop but continue to its ending position and finish taxiing. This is the trend seen in the data. The distance of aircraft 1 from its destination has a positive correlation to it being instructed to decelerate (Figure 7b) if it is a maximum of approximately 1500 meters from its destination after which the effect of this feature diminishes. This means that as the distance of aircraft 1 from its ending point increases, the likelihood of it being chosen to decelerate increases but after a threshold of about 1500 meters, other factors become more important. The SHAP values of the distance of aircraft 2 from its destination also support this. If aircraft 2 is close to its ending point, then until an approximate 1500 meter threshold, it is more likely for it to continue taxiing and for aircraft 1 to be chosen to decelerate. This is illustrated in Figure 8b. An aircraft close to its starting point is also found to be more likely to be chosen to decelerate. However, the feature's effect plateaus after it is 1000 meters away from its start.

Speed of aircraft: As seen in Figure 7c, there is a positive exponential relationship between the speed of aircraft 1 and its SHAP value. This means that a higher speed of aircraft 1 makes it more likely to be the one chosen to decelerate than when it is taxiing at a slower speed. Concurrently, the inverse is true for the speed of aircraft 2. A low value of speed 2 makes it more likely for aircraft 1 to be the faster one and be chosen to decelerate. This trend is depicted in Figure 8c.

Type of flight: The flight type feature has a very small feature importance value (refer to Figure 5). Figure 6 suggests that an arrival aircraft may be more likely to decelerate i.e. a departure aircraft will be

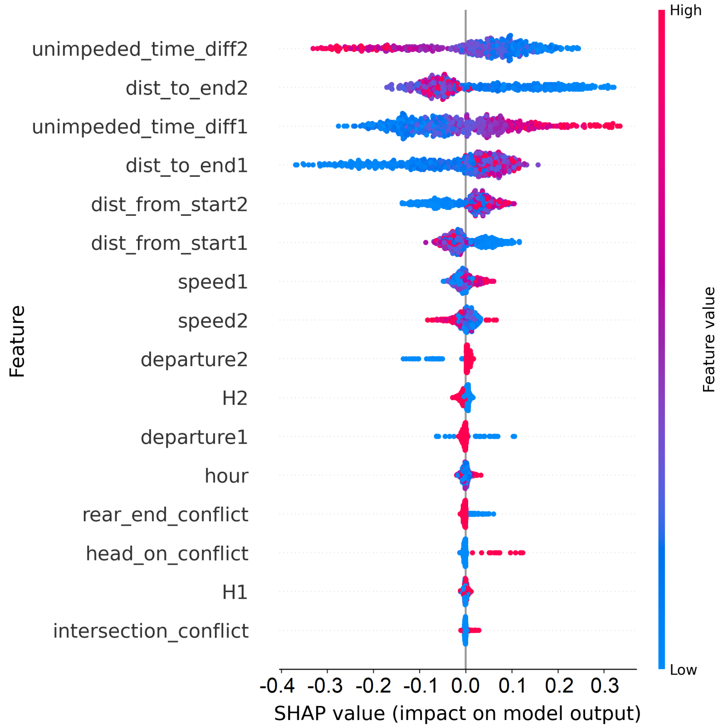
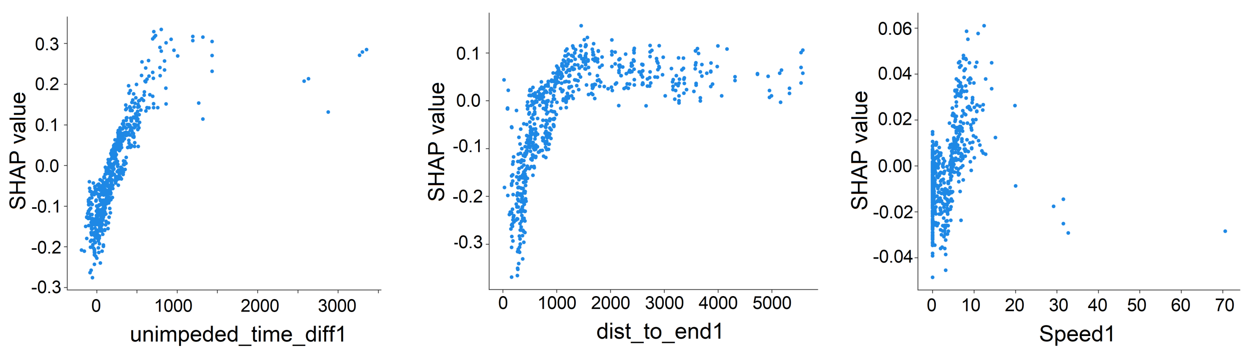


Figure 6: Summary plot of SHAP feature importance.



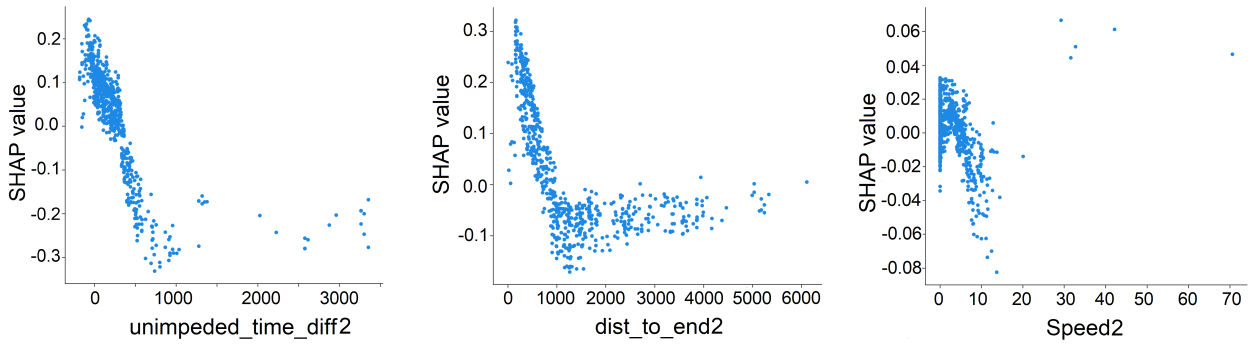
(a) Unimpeded time difference. (b) Distance to ending point. (c) Speed of aircraft.

Figure 7: SHAP values of aircraft 1 features.

given higher priority over an arrival aircraft. Intuitively, this can be attributed to departure aircraft having a stricter schedule to adhere to as a small delay in it can have a large domino effect on other flights. On further examination, the low feature importance of the flight type can be attributed to the dataset being highly dominated by departure aircraft ($\approx 90\%$ of the data). This also suggests that an arrival aircraft is much less likely to conflict and require an ATC's intervention when compared to a departure aircraft.

6 CONCLUSION

This paper presents a machine learning-based framework for aircraft priority assignment of taxiing aircraft during conflict resolution. ATC interventions are determined by identifying instances where an aircraft's



(a) Unimpeded time difference. (b) Distance to ending point. (c) Speed of aircraft.

Figure 8: SHAP values of aircraft 2 features.

average speed over 10 seconds is reduced by 80% or more (with a minimum reduction of 1m/s). The trajectory of the aircraft is calculated, assuming that the intervention did not occur and a conflict detection algorithm is run using this trajectory to identify the potential conflicts sans an intervention. Subsequently, a feature set is created for these avoided conflicts and used to train a random forest model to determine which aircraft is given lower priority by the ATC. Finally, the effect of all aircraft features in the model's prediction is analyzed.

The results obtained suggest that factors like aircraft speed, unimpeded time difference, and distance from start and destination primarily dictate aircraft priority. Higher speed and the unimpeded time difference made it more likely for an aircraft to be given lower priority. An aircraft closer to its start was more probable to be chosen to decelerate when less than 1000m from the start. Concurrently, an aircraft closer to its destination was less likely to be slowed down when less than 1500m from the destination. The model achieves a high overall accuracy of 88.9% in mimicking the ATC's decision-making on assigning aircraft priority when tested on data from a completely different week than which it was trained on. Hence, the framework effectively models an ATC's decision-making during conflict resolution.

In the future, we aim to compare the performance path scheduling and conflict resolution algorithms using our priority assignment with those using simple rules such as FCFS. Additionally, we would like to consider more factors that influence aircraft priority assignment such as if an aircraft is delayed, is a medivac flight, has a sick passenger or has to meet any time restriction. The data currently used do not have this information. Therefore, for our future work, we would like to incorporate ATC-pilot communication data and other data sources for better modeling of such circumstances.

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