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PREDICTING TERMINAL MID-AIR COLLISIONS THROUGH SIMULATOR EXPERIMENTS OF AIR TRAFFIC CONTROL

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ABSTRACT

The workload of air traffic controllers (ATCs) is increasing due to the growing air traffic. Early alarms of loss of separation (LoS) events between aircraft are critical for ATCs to coordinate intensive traffic safely. The authors studied the time series of traffic densities and numbers of turning aircraft in a given sky section as early indicators of pending LoS. Simulator experiment produced data for comparing the prediction accuracies of the logistic regression models generated from the time series of traffic densities and numbers of turning aircraft, and combinations of these two. We studied different sections of the time series to examine the possibility of early detection and found that 1) the regression model based on the traffic density time series is more accurate than the model using the numbers of turning aircraft; 2) properly combining sections of the time series could produce models that achieve earlier predictions without losing accuracy.

1 INTRODUCTION

Air traffic is a popular public transportation mode. In 2018, the number of people traveled through aircraft was over 1,000 million (BTS 2018). Efficient aircraft terminal approach operations are becoming increasingly important in air traffic management (ATM). According to the European Organization for the Safety of Air Navigation (EUROCONTROL), the gap between the current terminal airspace capacity and the forecasted air traffic demand will be around 152,000 flights by 2025. Operational bottlenecks at terminal airspace limit the growth of air traffic volumes by at least 1.2% (EUROCONTROL 2019). Improving the approaching operational efficiency at terminal airspace across the world is thus critical to narrow the gap between air traffic demand and the current capacity of the air transportation network.

In the aircraft terminal approaching process, the work performance of Air Traffic Controllers (ATCs) is a significant bottleneck on the capacity of the ATM system (Hilburn 2004). Improving the air traffic management performance of ATCs is vital to efficient terminal airspace operations. To ensure the safety of the airspace, ATCs take the responsibility of monitoring aircraft in mid-air and give appropriate navigating guidance to the pilots. ATCs must work on surveillance, communication, and decision-making tasks with strong coordination skills while striving to avoid errors. At the same time, with the high speed of aircraft in mid-air and crowed terminal airspace environments, ATC's work becomes "time pressure, multiple goals, interconnected tasks and high consequences of errors" (Kontogiannis and Malakis 2013).

With the increasing air traffic demands, the workload of ATCs will be more substantial. According to the data from U.S. BTS (Bureau of Transportation Statistics), the total amount of domestic flights in 2019 is up to 1,620,275, which is almost 1.6 times the number in 2002. At some busy airports, such as Hartsfield–Jackson Atlanta International Airport and Los Angeles International Airport, the amount of daily air traffic in one airport is over one thousand (FAA 2019).

How to relieve the workload of the ATC is crucial to handle the increasing traffic demands. The primary workloads of ATCs come from the separation assurance operation (Dwyer and Landry 2009). The separation assurance work of ATCs has two parts: 1) aircraft route design – the planning part of the work, and 2) assigning the designed route to pilots – the real-time control part of the work (Dwyer and Landry 2009). The goal of the separation assurance work is to keep the required distance between aircraft to avoid loss of separations (LoS) events, which are high-risk indicators of aircraft collisions (Chaloulos et al. 2010). Several studies focused on the aircraft route design in the collision avoidance system. For example, some researchers proposed generating aircraft route designs based on dynamic programming methods (Kochenderfer and Chryssanthacopoulos 2011). A few other researchers suggested map-based approaches or reinforcement learning for aircraft route design (Pham et al. 2019; Zhao et al. 2019).

To ensure that the pilots have enough time to follow the designed routes with proper reaction time buffers, ATCs need to inform pilots of the planned routes in advance (Gosling 2002). The time pressure requires the ATCs to have a sufficient situation awareness of pending LoS events based on their intuition or experiences. However, the current collision avoidance system cannot support the early predictions of LoS for enabling such timely communication between pilots and ATCs (Kearney et al. 2016). Previous studies mostly used numerical simulations, which may not consider the influence of the human's actual dynamic operations in the real-world (Yang et al. 2016; Cafieri and Rey 2017).

The research team aims at overcoming the limitation of numeric simulations by conducting a lab simulator experiment with six retired ATCs in a radar simulator on the polytechnical campus of Arizona State University. In each trial of the lab simulator experiment, a retired ATC and three aviation program students collaborated in controlling multiple aircraft that are approaching and leaving an airport per scenario set up in the simulator environment. Retired ATC will assume the role of ATC in Terminal Radar Approach Control (TRACON), while the students are pseudo pilots who will communicate with the ATC and control the aircraft under their responsibility based on the commands from the ATC. Such a simulator experiment keeps real humans in the simulation process and needs humans to make decisions and maintain the separations between aircraft. Thus, the outcomes of the simulator experiment are generated from real human decisions rather than pre-defined air traffic flows in many other computational simulations. To relieve ATC's time pressure to the maximum extent, the research team use the data collected in simulator experiment to study how different types of traffic features (e.g., traffic densities, numbers of turning aircraft) could help predict LoS based on the logistic regression method. The purpose is to find the time series of traffic features that could provide a reliable early prediction of LoS. The ultimate goal is to develop a model for supporting the early decisions of ATCs to handle pending LoS.

The paper explored the potential of using historical traffic data to support early predictions of LoS from two aspects: 1) using different historical traffic time series data as the inputs; 2) using different historical traffic time series data in different periods as the inputs. The aims of the paper are: 1) exploring the feasibility of using historical traffic data to predict LoS to support the ATCs' operational decisions; 2) exploring the historical traffic time series which has the potential to offer early detections of pending LoS without losing accuracy. The following sections of the paper will first present the methodology of examining various traffic features to identify features that could potentially support early detections of LoS, then illustrate the experiment design for collecting data to assess the proposed methodology, and then the results, discussions. The last section summarizes the findings and suggests future research directions.

2 METHODOLOGY FOR PREDICTING LOSS OF SEPARATION AND EVALUATION METRICS

This section offers a comprehensive introduction to the research methodology. Specifically, Section 2.1 illustrates the framework of the predicting LoS model and what are the input and output of the prediction model. Section 2.2 explains the calculation method in the prediction model. Section 2.3 clarifies the evaluation metrics of the prediction model's performance.

2.1 Scenario-based Model for Predicting Loss of Separation

ATC's situation awareness is highly related to traffic dynamics (Chaloulos et al. 2010), including traffic density and dynamic density (Prandini et al. 2011). Traffic density refers to the number of aircraft in a given sky section. Dynamic density refers to several traffic behavioral features, such as traffic flow structure, and the mix of aircraft types (Idris et al. 2009). Among those dynamic features, aircraft turning behavior is a frequently used analyzing factor in the collision prevention research (Durand et al. 1996; Hu et al. 2002; Fu et al. 2015; Liang 2018; Wang et al. 2020). Thus, this paper examines the relationship between traffic density, aircraft's behavior (turning aircraft), and LoS.

Figure 1 shows two scenarios of producing LoS prediction models. Scenario 1 explores 1) the feasibility of predicting loss of separation (LoS) events based on traffic features – in this study the time series of traffic densities and the numbers of turning aircraft; 2) the difference of the prediction performance based on the time series of different traffic features. Scenario 2 studies 1) how the selection of different periods of the traffic time series on the LoS prediction performance, and 2) how to achieve earlier predictions.

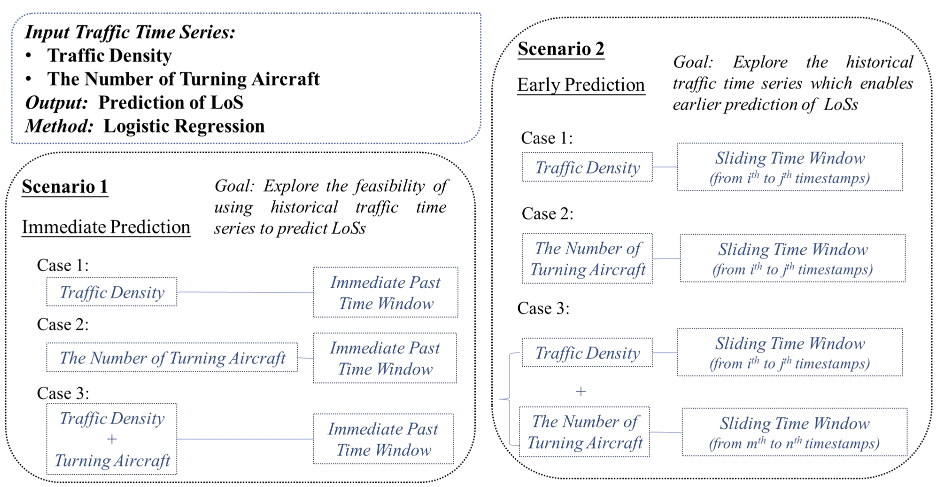


Figure 1: Scenario-based model for Predicting Loss of separation

In scenario 1, as shown in Figure 1, the input data of the model in the case 1 are the historical traffic density time series. The input data of the model in case 2 are the historical time series of the number of turning aircraft. The input data of the model in case 3 are the historical time series of traffic density and the number of turning aircraft. The output of the model is the prediction of whether a loss of separation event will happen in the next timestamps of the input time series. In other words, to explore the feasibility of predicting the LoS in the k^{th} timestamp, the cases in scenario 1 use the traffic time series from the immediate past time window as the input. In the paper, we set the k equals to 11, and the immediate past time window size equals to 10. To be more specific, the followings illustrate the first two samples in case

1 of scenario 1. In the first sample, the prediction model takes the traffic time series of traffic density from the 1st to 10th timestamps as the input. The output is the predicted loss of separation at the 11th timestamp. In the second sample, moving out the traffic density's data from the 1st timestamp and add the 11th timestamp's data to predict whether there is an LoS at the12th timestamp, and so on. Scenario 1 aims to explore whether it is possible to predict losses of separation based on the historical traffic density or the number of turning aircraft. If the model works, then it is possible to provide loss of separation alarming to the ATCs in advance.

Scenario 2, as shown in Figure 1, aims to explore which traffic time series has the potential to offer an earlier prediction of LoS. The early prediction of LoS could offer ATCs more time to deliver the designed separation route to pilots. Same as scenario 1, each case takes different input traffic time series. Instead of using traffic time series in the immediate past time window, the prediction model in scenario 2 changes the time window of the input to find the case with the potential to give an earlier prediction. To be more specific, take case 1 as an example. The output will be the predicted situation of the loss of separation at the k^{th} timestamp, which is the same as scenario 1 (the 11th timestamp). The inputs of the samples in case 1 of scenario 2 are the historical time series of traffic density in the time window that starts from the i^{th} timestamp to the j^{th} timestamp with the restriction shown in the equation (1).

$$0 < i \leq j \leq k - 1 \tag{1}$$

Figure 2 shows the calculation steps in case 1 of scenario 2. The prediction model will find the *i* and *j* with the highest accuracy and F1 score in both case 1 and case 2 through iteratively changing the values of i and j. The calculation steps in case 2 of scenario 2 are the same, while the input is the time series of the number of turning aircraft instead of traffic density.

```
for i in range(1, (k-1)):
    for j in range(1, (k-1)):
        if j>=i:
            read the traffic density/ turning aircraft data from timestamp i th to j th as input data
            input the data into the loss of separation prediction model
            output the prediction of loss of separation at the kth timestamp
            evaluate the prediction results based on accuracy rate and F1 score
```

Figure 2: Pseudo-code for sliding time windows in case 1 and case 2 of scenario 2

Figure 3 shows the calculation steps in case 3 of scenario 2. Since, in case 3, the inputs of the prediction model are two types of traffic time series, traffic density and the number of turning aircraft, the iteration of the time windows in the case 3 would have one more round than the iteration in the case 1 and case 2. In other words, for each input time series of traffic density from i^{th} to j^{th} timestamp, we will iterate the input time series of the number of turning aircraft from m^{th} to n^{th} with restriction shown in the equation (2).

$$0 < m \leq n \leq k - 1 \tag{2}$$

```
for i in range (1, (k-1)):
    for j in range (1, (k-1)):
        if j>=i:
            read the traffic density data from timestamp i th to j th as one part of the input data
                for m in range (1, (k-1)):
                    for n in range (1, (k-1)):
                        if n>=m:
                            read the number of turning aircraft data from timestamp m th to n th as the other part of the input data
                            input the two part of data into the loss of separation prediction model
                            output the prediction of loss of separation at the kth timestamp
                            evaluate the prediction results based on accuracy rate and F1 score
```

Figure 3: Pseudo-code for sliding time windows in case 3 of scenario 2

Scenario 2 explores the prediction model with the earliest input traffic density through two parts:1) find the maximum leading time, where the leading time is the period between the recorded timestamps of the traffic time series and the timestamp where LoS occur, as shown in the equation (3); 2) find the minimum time window size of the input traffic time series, as shown in the equation (4). The cases with the maximum leading time and minimum window size could offer us an earlier detection of the pending LoS with the minimum computation cost.

$$\text{Case} \leftarrow \underset{i,j,m,n}{\text{argmax}} [k - \max\ (j, n)] \tag{3}$$

$$\text{Case} \leftarrow \underset{i,j,m,n}{\text{argmin}} [\max\ (j, n) - \max\ (i, m)] \tag{4}$$

2.2 Logistic Regression Method

The research team implemented a logistic regression method to predict the loss of separation, as shown in Figure 4. The logistic regression method performs well in the classification problem (Press and Wilson 1978). The output of the prediction model is binary, which belongs to the classification problem. The calculation process is illustrated in equation (5) and (6).

$$B = \frac{1}{1 + \exp\ (-A \cdot W)} \tag{5}$$

$$C = \begin{cases} 1, & \text{if } B > 0.5 \\ 0, & \text{if } B \leq 0.5 \end{cases} \tag{6}$$

In equation (5) and (6), A represents the input data, and C represents the output data. W is the best weight parameters through the gradient descent method measured by the cross-entropy function. At the output layer, 0 represents there is no loss of separation, and "1" represents that there is an LoS. Traffic density at each timestamp and the number of the turning aircraft at each timestamp are the input data. The detailed measurement of the traffic density and the number of turning aircraft is illustrated in Section 3.

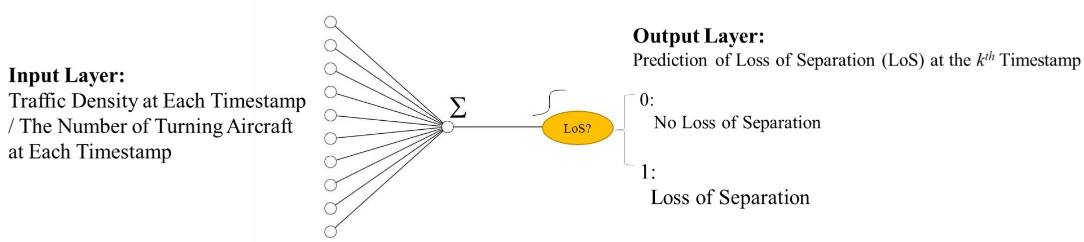


Figure 4: The structure of the Predicting Loss of Separation (LoS) method

2.3 Evaluation Metrics

This paper used two evaluation metrics, accuracy, and F1 score. The calculations of the accuracy and F1 score are shown in equation (7) and (8). The variables, precision, and recall, shown in the equation (8) are given by the equation (9) and (10).

$$Accuracy = \frac{\sum True\,Positive + \sum True\,Negative}{\sum Total\,Sample} \tag{7}$$

$$F1\,Score = \frac{Precision \cdot Recall}{Precision + Recall} \tag{8}$$

$$Precision = \frac{\sum True\,Positive}{\sum Predicted\,Condition\,Positive} \tag{9}$$

$$Recall = \frac{\sum True\,Positive}{\sum Condition\,Positive} \tag{10}$$

The accuracy measures the accuracy level of the whole model in the prediction of loss of separation or not. The F1 score measures the reliability of the prediction of loss of separation in the model. The higher the accuracy and F1 score, the more accurate and reliable the prediction model is. In the end, a highly accurate and reliable prediction model could help to relieve the ATC's situation awareness workload.

3 EXPERIMENT DESIGN

The research team conducted an experiment with six retired air traffic controllers in a radar simulator located on the polytechnical campus of Arizona State University. The lab experiment simulates the terminal approach process. As shown in Figure 5, each trial of the experiment included three pseudo pilots who each controlled multiple aircraft. Each trial has a single retired air traffic controller monitored and guided all pilots in driving the aircraft. Retired ATCs with experience at an FAA (Federal Aviation Administration) Terminal Radar Approach Control (TRACON) facility within the last 15 years ensured baseline familiarly with role and standard airspace system infrastructure. Each retired ATC took part in three simulated scenarios, "baseline," "high workload nominate," and "high off nominate," as defined in Figure 5.

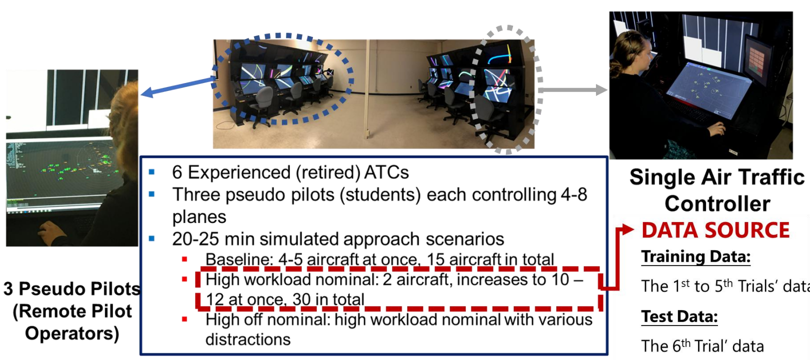


Figure 5: ATC simulated experiment to collect the data

As shown in Figure 5, in one trial, an ATC who controlled one simulator can monitor and guide pilots in operating aircraft in the airspace as an ATC radar workstation in a TRACON facility. Three pseudo pilots controlled the movement of these simulated aircraft. ATC contacted the pseudo pilots through radio communication. ATC guided pseudo pilots to operate aircraft movement to their destinations without LoS. ATC's simulator recorded the location of each aircraft every five seconds with a continuous timestamp, which is similar to the radar system in the real-world. To better understand how the high traffic volumes evolve in the terminal space impacts the mid-air collision, the authors analyzed data from the six high-workload nominal scenarios. The raw data used for model development is the trajectories of aircraft in the six high-workload nominal trials. The number of aircraft in the airspace at each timestamp is the data that represents the traffic density. Each aircraft with a heading angle of more than 5 degrees is counted as a turning aircraft. The number of aircraft which are making turns at each timestamp is noted in the data.

As shown in Figure 5, this paper analyzed the feasibility of predicting LoS events based on the data from high workload nominal scenarios. The authors plan to analyze the rest scenarios in the future. The training data (the first to the fifth trials) contains 1455 samples, and the test data (the sixth trials) contains 287 samples. The label of the data is 0 for no LoS event and 1 for otherwise. The LoS events are defined by breaches in separation minima of less than 5 nm radius and +/- 1000 foot vertical distance following the air traffic management regulation (ICAO 2016). Even though our data comes from an experiment, the simulated process is similar to the real-world operation. Besides, the high workload nominal scenarios could simulate the future terminal operation under high traffic volumes. Thus, the collected data can be suitable for training models to predict real-world LoS too. More details of the experiment are in (Ligda et al. 2019).

4 RESULTS AND DISCUSSIONS

Based on the simulator experiment in a radar simulator, the research team collected a time series of traffic densities, the number of aircraft that are making turns, and occurrences of LoS. These time series could train logistic regression-based machine learning models. The research team examined the prediction performance under two scenarios of using the time series in training models using the logistic regression method. The aims of the research are: 1) exploring the feasibility of using historical traffic data to predict loss of separation in the future to support the ATCs in the detection of pending LoS; 2) exploring the historical traffic time series which has the potential to offer the earlier detection of pending LoS.

4.1 Scenario 1: Immediate Prediction Performance

The model in scenario 1 used the traffic time series from the immediate past time window to predict the loss of separation at the k^{th} timestamp, where the size of the time window is ten (10), and *k* equals to 11 in this case. The results of scenario 1 are shown in Table 1. Case 1, which used the traffic density as the input, has higher accuracy and F1 score than case 2. However, the prediction model in case 2 still has a certain accuracy, as shown in Table 1. Case 1 and case 2 both show that the historical data of traffic density and turning aircraft could serve as the indicator of pending loss of separation. Case 3 has the highest accuracy and F1 score, which implies that combining multiple traffic time series could achieve a more reliable and accurate prediction.

Table 1: The evaluation results of the Prediction of LoS in scenario 1

	Scenario 1: Case 1 (Traffic Density)	Scenario 1: Case 2 (The Number of Turning Aircraft)	Scenario 1:Case 3 (Traffic Density + The Number of Turning Aircraft)
Accuarcy	0.84669	0.60976	0.85017
F1 Score	0.85135	0.66864	0.85324

4.2 Scenario 2: Early Prediction Performance

Scenario 2 iteratively changes the time window inside the 1^{st} to $(k\text{-}1)^{th}$ timestamp to predict the loss of separation at the k^{th} timestamp (11^{th} timestamp). In order to present the result clearly, partial results in scenario 2 are shown in Figure 6 and Figure 7. Figure 6 and Figure 7 both reflect that the input traffic time series from different time windows could influence the prediction of loss of separation. However, the impacts from the same time window of the different traffic features are different, as shown in Figure 6 and Figure 7. Figure 6 shows that the closer the time window is to the k^{th} timestamp (11^{th} timestamp), the higher the accuracy and F1 score of the model are, which indicates that the less leading time of traffic density, the better performance of the prediction. Figure 7 shows that the closer the time window is to the

k^{th} timestamp (11th timestamp), the lower accuracy and F1 score of the model are. Especially when the input data coming from the 8th to10th timestamp, the accuracy of the model could drop below 0.5. The result reveals that the same historical time series of different types of traffic data has a different influence on the prediction of LoS. The full results of case 1 and case 2 in scenario 2 are shown in Figure 8 and Figure 9.

Figure 8 shows the results of all possible combination of *i* and *j* in case 1 of scenario 2. The traffic density data starts from the 8th to 9th could support the prediction of LoS at the 11th timestamp to achieve the highest accuracy and F1 score. Figure 9 shows the results of all possible combination of *i* and *j* in case 2 of scenario 2. The time series of the number of turning aircraft starts from the 1st to 8th could support the prediction of loss of separation to achieve the highest accuracy and F1 score. To be more specific, the model trained by the time-series of traffic densities could achieve the best prediction accuracy (87%) by using traffic density data collected within 5 seconds before the LoS occurrence. On the contrary, the model trained by the time series of the numbers of turning aircraft achieves the best prediction accuracy (65%) using the data points collected more than 10 seconds before the occurrence LoS.

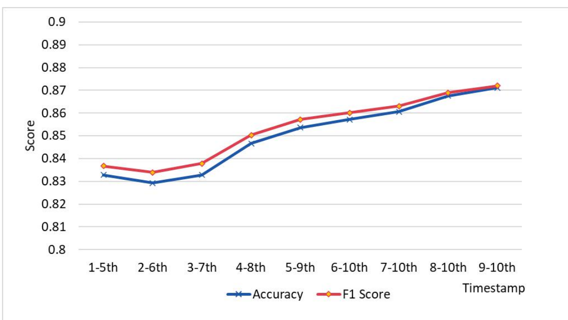


Figure 6: Traffic density's influence on the Prediction of LoS at 11th timestamp based on different time windows

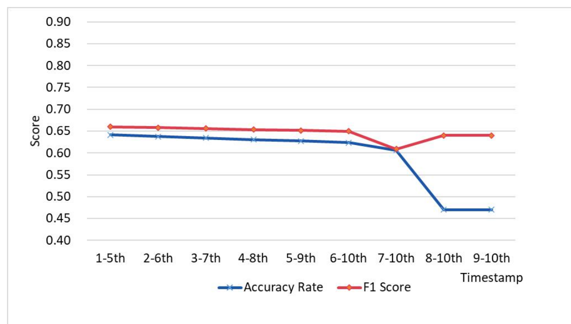
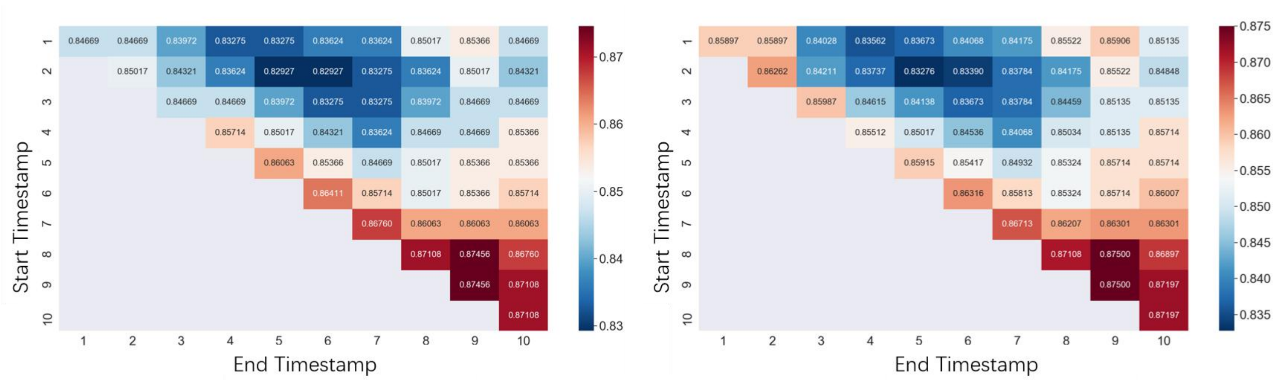


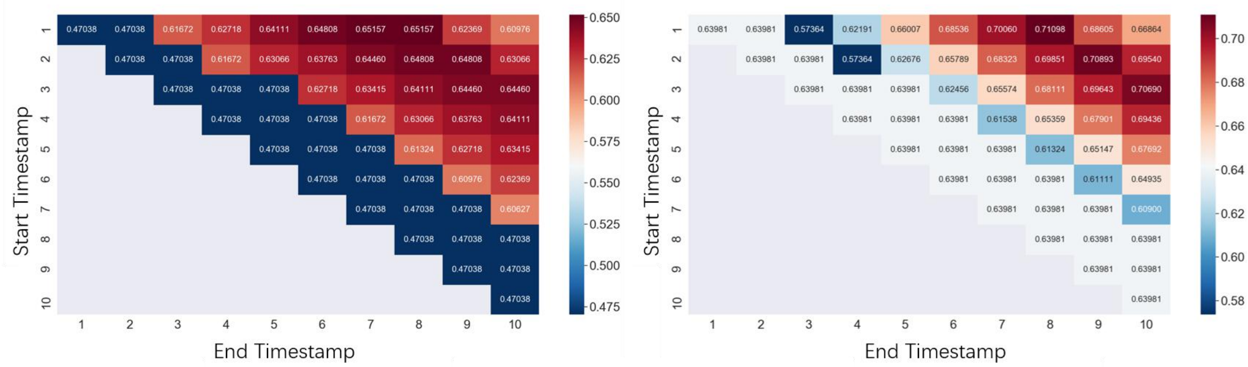
Figure 7: The number of turning aircraft's influence on the Prediction of LoS at 11th timestamp based on different time windows



(a) Accuracy

(b) F1 Score

Figure 8: The accuracy and F1 Score in case 1 of scenario 2



(a) Accuracy (b) F1 Score

Figure 9: The accuracy and F1 Score in case 2 of scenario 2

Figure 10 and Figure 11 show the results of the all possible combination of *i*, *j*, *m*, and *n* in case 3 of scenario 2. The traffic density of the 8th timestamp combining with the number of turning aircraft from 1st to 3rd timestamp could support the prediction of LoS to achieve the highest accuracy and F1 score. To be more specific, the model trained with different time series of traffic density and the number of turning aircraft could achieve high accuracy, which is up to 0.87456. Meanwhile, the model with the highest accuracy can provide the prediction 10 seconds ahead of the occurrence of LoS. It is worth to the point that some combinations of the time series also offer high accuracy and provide even earlier detection of LoS.

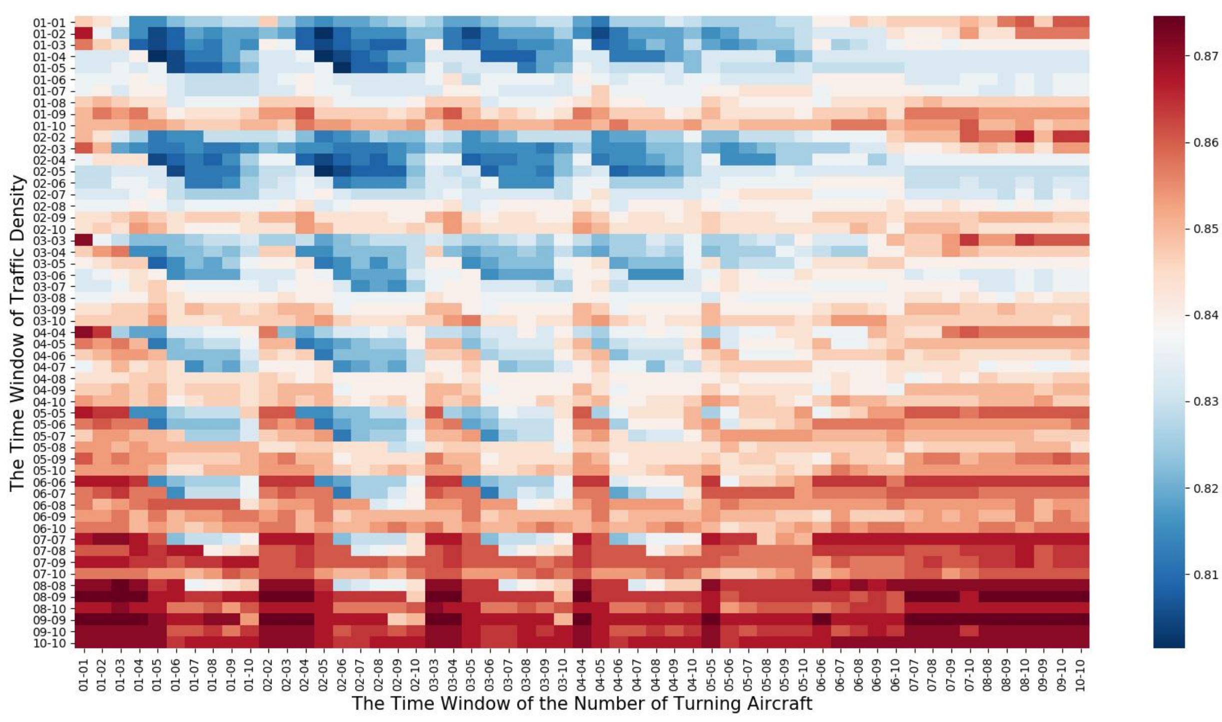


Figure 10: The accuracy in case 3 of scenario 2

For example, the model with the input time series from the traffic density in the 4th timestamp and the number of turning aircraft in the 1st timestamp could also achieve accuracy at 0.87108. Even though this combination did not offer the highest accuracy, it still holds a high accuracy and even provides earlier detections of the LoS. The study would explore more about how to maintain accuracy and provide earlier detections of LoS in the future.

Figure 12 shows the comparison result of the highest accuracy and F1 score of all cases in each scenario. The traffic density of 8th timestamp combining with the number of turning aircraft from 1st to 3rd timestamp in case 3 of scenario 2could support the prediction of LoS to achieve the highest accuracy and F1 score, which are 0.87456 and 0.87586, respectively. Comparison to the results in the scenario 1, the case 3 in scenario 2 also enables the earlier detection, since the latest traffic time series in the model is 8th instead of 10th, which means the model in case 3 of scenario 2offers an accurate prediction of LoS 10 seconds ahead of the prediction models in the scenario 1. The result shows the potential for an early accurate prediction of LoS by using the combination of the traffic density time series and the number of turning aircraft time series from different time windows.

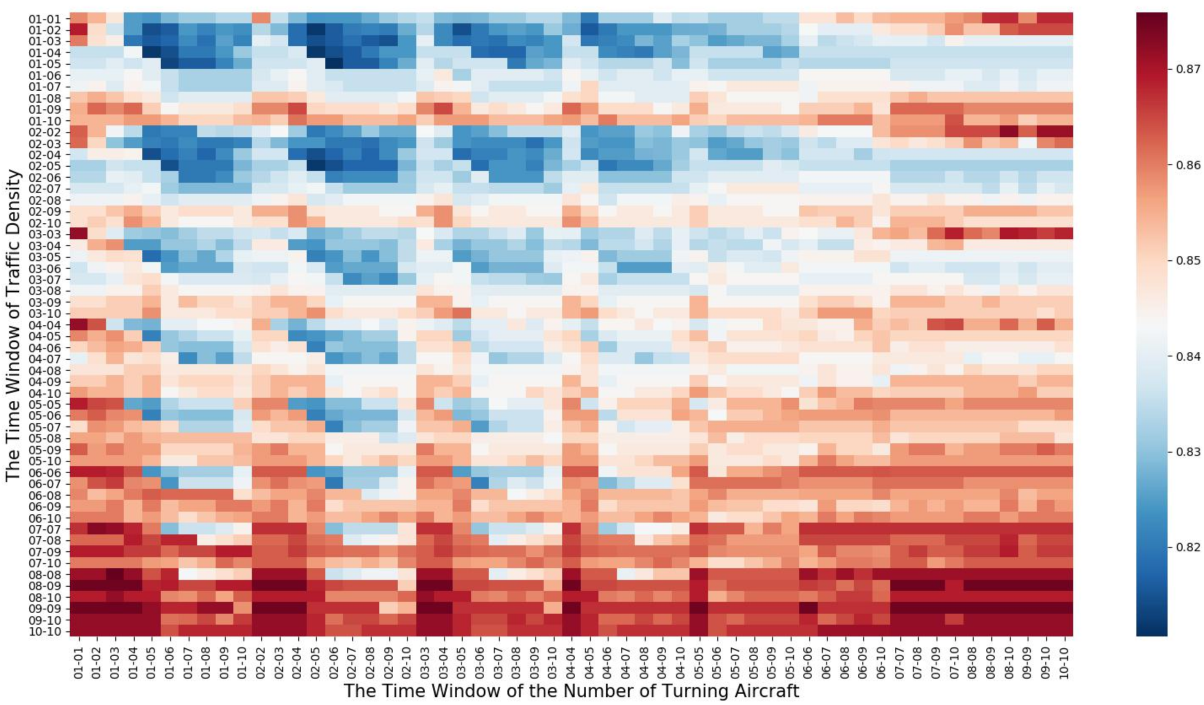


Figure 11: The F1 Score in case 3 of scenario 2

5 CONCLUSIONS

In order to enhance the ATCs' situation awareness to avoid mid-air collisions, this paper developed a model for predicting loss of separation. Further, in order to explore the historical traffic time series, which has the potential to offer the early detection of pending LoS, this paper constructs the prediction model with multiple cases. The results show that the model trained by the time-series of traffic densities could achieve the best prediction accuracy (87%) by using traffic density data collected within 5 seconds before the LoS occurrence. On the contrary, the model trained by the time series of the numbers of turning aircraft achieve the best prediction accuracy (65%) using the data points collected more than 10 seconds before the occurrence LoS. The results also show that with the integration of historical traffic time series, the prediction model can achieve an earlier detection (10 seconds ahead) with the same accuracy (87%).

The overall conclusions include: 1) the historical traffic density and turning aircraft could serve as an indicator to predict loss of separation; 2) different types of traffic features with the same periods of time series have different influences on the prediction of LoS; 3) combination of traffic density and number of turning aircraft has more potential for an accurate precursor detection and early alarming of LoS. Such a combination offers prediction accuracy up to 87.5% and provides the prediction of LoS 10 seconds ahead of the occurrence.

Future research will further develop the model along with the following directions: 1) Exploring the possibility of providing earlier prediction of LoS (more than 10 seconds) without losing accuracy under various dynamic environments, such as high off nominate scenarios mentioned in the experiment design; 2) Improving the performance of the model through the adjustment of the learning algorithms. The goal is to limit the false positive and false negative to relieve the ATC's workload with a reliable and accurate model. 3) Considering more factors in the dynamic density, such as the mix of aircraft types and performance characteristics(Idris et al. 2009) and establishing a criterion of feature selection. Through the fore-mentioned development, the model would not have too much redundancy computation, which can make the model more reliable and efficient at the same time.

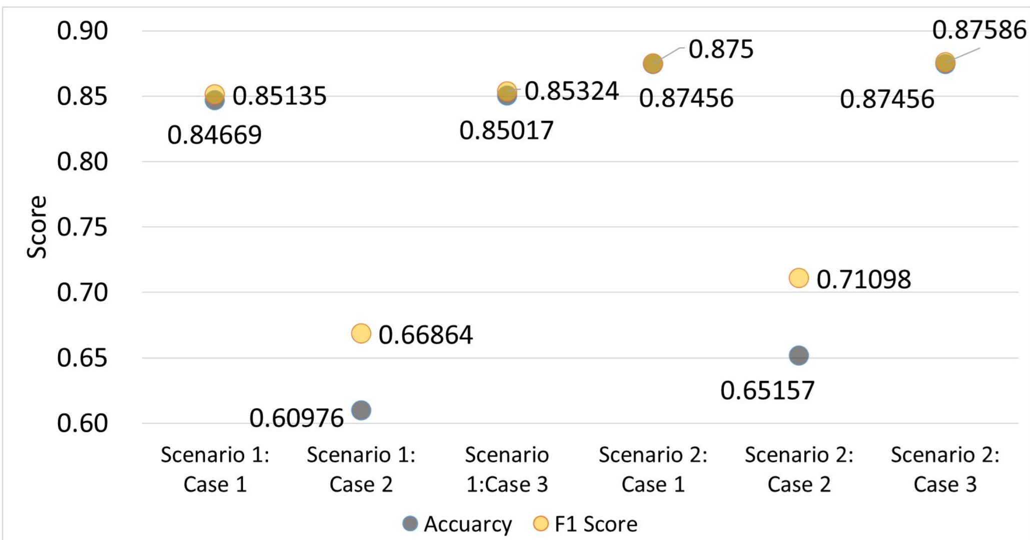


Figure 12: The comparison of accuracy and F1 Score of cases in scenarios

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